Ergodesign & HCI
número 1, volume 10, jan-jun (2022)

PUC-Rio Pontifícia Universidade Católica do Rio de Janeiro
Departamento de Artes & Design | PPGDesign
LEUI | Laboratório de Ergodesign e Usabilidade de Interfaces

THE PARTICIPATION OF UX DESIGNERS IN ARTIFICIAL INTELLIGENCE PROJECTS: RECOMMENDER SYSTEMS

A PARTICIPAÇÃO DOS UX DESIGNERS EM PROJETOS DE INTELIGÊNCIA ARTIFICIAL: SISTEMAS DE RECOMENDAÇÃO

Cinthia Ruiz[1], D.Sc.
cinthiaruiz@gmail.com and http://orcid.org/0000-0002-0876-1774
Manuela Quaresma[1], D.Sc.
mquaresma@puc-rio.br and http://orcid.org/0000-0001-5683-7692

[1] Laboratório de Ergodesign e Usabilidade de Interfaces, PUC-Rio, Rio de Janeiro, Brasil

UX designer, recommender system, artificial intelligence, machine learning

With technological advances, artificial intelligence has gained prominence and we increasingly find innovative products on the market, bringing it as a differential. One example is machine learning-based recommender systems, which filter content in a personalized way for each user, saving the user's time and cognitive effort. Like any novelty, the professional market is still maturing, and users are learning to interact with interfaces. The performance of a UX designer becomes relevant to ensure a good user experience. Therefore, it is important to investigate the market to map the participation of the UX designer in the development of products that use a recommendation system. For this purpose, this research involved market professionals in interviews to understand the UX Designer's participation in developing recommendation systems based on machine learning and identified several relevant issues that point to the need to focus on human factors. It also indicates the training of professionals, the generation of content on the theme of AI/ML aimed at designers and working on the culture of companies.

UX designer, sistema de recomendação, inteligência artificial, aprendizado de máquina

Com o avanço tecnológico, a inteligência artificial ganhou protagonismo e cada vez mais encontramos produtos inovadores no mercado, trazendo-a como diferencial. Um exemplo são sistemas de recomendação baseados em aprendizado de máquina, que filtram o conteúdo de maneira personalizada para cada usuário, poupando tempo e esforço cognitivo do usuário. Como toda novidade, o mercado profissional ainda está em amadurecimento e os usuários estão aprendendo a interagir com as interfaces. A atuação do UX designer torna-se relevante para garantir uma boa experiência de uso. Por isso, é importante investigar o mercado para mapear o envolvimento do UX designer no desenvolvimento de produtos que utilizem sistema de recomendação. Com esse propósito, esta pesquisa envolveu profissionais de mercado em entrevistas, para entender o envolvimento do UX Designer no processo de desenvolvimento de sistemas de recomendação baseados em aprendizado de máquina e identificou diversas questões relevantes que apontam para a necessidade de dar foco aos fatores humanos. Também indica a capacitação dos profissionais, a geração de conteúdo no tema de AI/ML voltado para designers e trabalhar a cultura das empresas.

Recebido em: 28 / 04 / 2022
Aceito em: 17 / 05 / 2022
DOI: http://dx.doi.org/10.22570/ergodesignhci.v10i1.1750

1. Introduction

Artificial intelligence (AI) is not new, but it has gained a lot of strength in recent years and has re-emerged as a basis for innovative products, which directly impact the user experience with digital interfaces. Rouhiainen (2018) says that AI is the ability of machines to use algorithms to learn from data and use what has been learned to make decisions as a human being would. Machines can analyze a lot of data at once and more accurately than humans. The author exposes that machine learning (ML) is one of the main approaches to artificial intelligence, with which machines can learn from data without being explicitly programmed. As a result, suggestions or predictions are presented for a specific situation, which allows for a personalized experience for each user.

ML expertise is already present in many of the innovative interfaces we interact with, such as search engines, recommended e-commerce links, audio or video streaming systems, face detection, tax fraud detection, information technology security, car automation, medical applications, etc. ML algorithms are dramatically changing the way we interact and how we build systems. Before, we needed to plan the best information architecture, so that users could find their way through the entire volume of content and reach their choices, considering their mental model. Now, we have ML algorithms filtering the content and selecting the most appropriate for each profile, according to the trained models based on the available data.

Technologically, a lot has already been evolved and there is still a lot to evolve, mainly in the human factors involved in these human-computer systems. Currently, it appears that AI/ML evolutions are still very much technology-driven, driven by the technology's capability rather than the needs of its users. It is possible that design methods can be employed to improve users' experience with AI-based digital systems.

This article proposes to present a market investigation, to understand how the UX designer is a participant in the development of interfaces with an ML-based recommendation system and to identify the relevance of its role and its difficulties in this process. In this context, semi-structured interviews were carried out with market professionals.

2. Artificial Intelligence and Machine Learning

Springer, Hollis and Whittaker (2017) emphasize that hidden algorithms increasingly govern our lives, as they make decisions for us, directly influencing our behavior. In reality, the final decision is up to the user, but the degree of influence is directly related to the degree of trust the user places in the system. Likewise, the convenience of using the system also impacts user engagement.

ML-based recommender systems seek to offer the user a direct path to content suited to his or her profile. The ML algorithm proposes to know the user, learn from him and make increasingly accurate predictions of the type of content he would choose, based on behavior data analysis and comparisons. This operation seems ideal for a human-centric design, as it saves the user's cognitive effort and decision-making time, presenting personalized navigation for each individual. In practice, some possible problems are already studied by researchers, such as the formation of bubbles, loss of control, weak mental model, and lack of transparency, among others. Konstan and Riedl (2012) indicate that a strong point of recommender systems is the fact that they reduce the workload of users in the face of so many available options. However, they claim that users are generally happier when they are in control of the system, even if it takes more effort.

According to Aggarwal (2016), recommender systems gain importance in the 90s, due to the use of the Web for commercial and e-commerce transactions. Innovation is personalization based on data collection, unfeasible in other ways. The basic idea here is to infer users' interests based on various data sources. In the case of VoD platforms, such sources can be explicit feedback, when the user marks the “like” or implicit, when the user watches a movie and the system interprets that he likes that type of content, or similar.

Therefore, the analysis considers the interaction between users and content, as it assumes that past choices and trends are good indicators of future choices. For their functioning, recommender systems use collaborative filtering methods, content-based methods and knowledge-based methods. The author explains that collaborative filtering methods consider user-item interactions, such as ratings or purchase behavior. Content-based methods consider attribute information about users and items, such as textual profiles or relevant keywords. In knowledge-based systems, recommendations consider explicitly specified user requirements rather than their history. There are also hybrid systems that can combine the strengths of several types of recommender systems.

To maintain user engagement, the recommender system needs to be accurate. To fulfill this objective, it must select content relevant to the user, in addition to presenting news, that is, content not yet watched by the user, but adhering to their interest. Another important factor is the originality, with contents that positively surprise you. Occurs when content is not obvious according to his profile, but that captures his interest. Finally, the diversity in the types of content presented increases the chances of one being chosen and avoids the boredom of a selection with items that are very similar to each other.

Although ML systems seem autonomous when making decisions, they are made for humans and by humans. These are human decisions that drive data processing and mining, the selection of optimization goals, and the designed dialogue with end-users with their implicit and explicit feedback mechanisms. In this way, they are influenced by humans, from design decisions to interaction. According to Cramer and Thorn (2017), human decisions affect the results of ML systems in virtually every step of the process. Therefore, there is already a lot of recent research investigating the problems that occur in user interaction with AI-based systems.

Bodegraven (2017) relates what Eli Pariser described as “the filter bubble” in 2011, about how the personalized web influenced people’s reading and thinking, with predictive systems. He believes the same risk applies when devices anticipate our needs. An experience bubble is formed in which the user is trapped in an interaction cycle with the content. Google PAIR (2019) states that there are many situations where people prefer AI to just broaden their skills rather than completely automating a task. Bodegraven (2017) concludes that the design principles of renowned researchers (such as the 10 usability heuristics) are insufficient for automation, as they disregard the principles of transparency, control, loops and privacy, but reinforces that UX design is fundamental to offering the user an unprecedented and predictive experience with technology.

In addition, Budiu (2018) warns that the lack of transparency of the algorithms hinders users' understanding of how the system works, as they do not know how much the recommendations are random or influenced by their interaction. This fact is exacerbated because user actions do not immediately impact the result of recommendations. The recommendation systems of ML-based VoD platforms are considered black boxes, which then impairs the formation of the users' mental model of how it works.

Bodegraven (2017) also warns about data privacy: users tend to think they "have nothing to hide", and companies are increasingly sharing user data without them knowing and realizing the consequences. Google PAIR (2019) suggests that the system explains to users the origin of the data and how it is used by the AI system, so as not to undermine trust. This is because users can be surprised at their information when they see it in a new context, often in a way that appears to be non-private or otherwise unaware of the system's access.

AI is not new, but it has found a very favorable scenario for its resumption and evolution, with the technological advancement of recent years and market opportunities. While it brings many benefits, solutions for user interaction with AI-based systems are still in the process of maturing. There are already studies to design a good user experience with AI systems, demonstrating that the market and academia are concerned about focusing on users' needs.

3. Innovation with Artificial Intelligence

Revista Ergodesign & HCI
ISSN 2317-8876

Norman and Verganti (2014) agreed with the importance of human-centered design for incremental innovation and its weakness in radical innovation, which would be motivated by the evolution of technology. For the authors, human-centered design tends to assume that innovation must arise from the observation of users. User needs are analyzed and technologies or means that can satisfy them are sought. An iterative process of prototyping and testing then begins until a usable and understandable product is achieved. The point is that several successful radical innovations did not originate in this way. All those identified by the authors were leveraged by the new possibilities of technology, without any formal user research basis.

According to Verganti, Vendraminelli and Iansiti (2020), decisions occupy the central point in an innovation process and have always been made by humans, but now they can be made by AI algorithms. The people-centered design assumes understanding a problem from the user's perspective and predicting what would be meaningful to the user, rather than innovation being driven by advances in technology and its possibilities.

The authors assume that AI changes design practice as some design decisions traditionally performed by designers are now automated in learning cycles. Interaction data is collected in real-time and processed immediately by the AI built into the product. An algorithm can autonomously generate a new solution specific to each user, without any human effort involved. As new data is continuously collected and the AI engine incorporates learning capabilities, problem-solving cycles improve their predictions about user needs and behaviors and design better solutions. The human no longer designs the final solution with all the details, but the parameters for the AI to design the custom interface. The problem is that designers weren't educated to design this way. In addition to imagining how the system will work at scale, the steps of the traditional design process – design, delivery and use – now occur simultaneously.

Dove et al. (2017) also claim that it is difficult for designers to work with ML, as their prototyping tools are unsuitable for ML projects, as they do not help to understand the UX impact of false-negative and false-positive responses. The authors say it's possible that UX designers don't have a clear understanding of what ML is and what it's capable of. Verganti, Vendraminelli, and Iansiti (2020) further concluded that in the same way that AI drives an improved design practice, design can also drive more effective and human-centered implementation of AI.

The employment of ML appears to have been driven primarily by the availability of data and technological advances, rather than arising from a user need and following a human-centric view. The role of the UX designer and investments in user studies are fundamental to designing good solutions. Google PAIR (2019) indicates that one must find the intersection of user needs and AI strengths, to solve real problems and AI adds value.

Endsley and Jones (2004) report that traditionally, systems are designed and developed to perform their function from a technology-centric perspective. The authors report that technical designers disregard the human processing of information, which generates an overload in the mental process of users when interacting with these systems. Many of the errors attributed to humans come from improperly designed technology. The authors also argue that the way to design more effective systems is to apply user-centered design, which challenges designers to shape the interface around the resources and needs of users, to obtain the optimal functioning of the entire human-machine system. In this way, errors are minimized and productivity improved, as well as user acceptance and satisfaction.

According to Barbosa et al. (2021), each area of knowledge has its perspective on experiences, solution strategies and established knowledge. They indicate that Software Engineering aims to build efficient, robust, error-free and easy-to-maintain interactive systems. On the other hand, the Human-Computer Interaction (HCI) area seeks the quality of use of these systems from the users' point of view. In this sense, if the software is built only with the Software Engineering vision without being completed with the HCI vision, it is possible to have a great system in terms of development, but difficult to be understood and used by the user.

Holzinger (2018) argues that ML design needs to combine HCI – Human-Computer Interaction – rooted in cognitive science, related to human intelligence; and KDD – Knowledge Discovery / Data Mining – rooted in computer science, related to artificial intelligence. The author reinforces the need to bring the user's vision to the technology.

Yang (2017) assumes that designers still do not have the practice, knowledge and tools suitable for ML projects. Cramer and Thorn (2017) also point out that design decisions affect ML results and human-computer interaction. Therefore, designers must participate in ML projects to improve user experience.

Generally, technology products are launched with a strong focus on functionality. Then, value is given to their usage needs and the user experience is considered. Regardless of the technology, any digital interface should be designed with a human focus to work according to the mental model of its users and ensure a good experience for them, including ML systems. As it is a field in recent expansion, it brings new challenges to designers and there is still a lot of research, maturation and evolution. PAIR also indicates that the focus is on people rather than technology: shifting from technology-first to people-first thinking.

The process of developing ML interfaces is very focused on the technological capability of the tool, but to ensure a good user experience, it is necessary to focus on people's needs. We need to understand what it's like for people to interact with ML interfaces and what needs they're meeting. In addition, we need to identify design challenges and know how to solve them.

4. Method

Dove et al. (2017) have the view that technology generally enters the market without much concern for design. Designers would then participate in the technology maturation process. Added to this is the argument by Verganti, Vendraminelli and Iansiti (2020), that the design process for AI interfaces has particularities, not yet very common to designers. Yang (2017) believes that designers still do not have the practice, knowledge and tools suitable for ML projects. Cramer and Thorn (2017) advocate that designers get participation in ML projects, aiming to improve the user experience.

To understand how UX Designer participates in the development of interfaces based on ML, with a recommender system, semi-structured interviews were planned with professional participants in the development of interfaces with a recommender system based on AI/ML. In this way, there would be flexibility to explore the arguments of the interviewees and develop the interview based on the findings that emerged. We sought to explore the following questions:

1. At what stages and for what purposes do UX professionals participate in projects?
2. What are the methods used to deal with the experience?
3. What are the difficulties of UX designers with AI/ML projects?
4. What are the differences between designing an interface with and without ML?

According to Martin and Hanington (2012), the interview is a fundamental method of research to have direct contact with participants, through which experiences, opinions, attitudes and perceptions can be collected. 20 participants were selected from the professional profiles of UX designers, data scientists, developers and product managers, participants in the development and maintenance of AI-based recommender systems. The number was defined by the saturation of responses, which according to Guest, Bunce and Johnson (2006) is the point at which no new information or new theme is inserted into the data. The sampling method was non-probabilistic – initially, participants were recruited by LinkedIn and the snowball method was used for continuity. The interviews were conducted remotely with recording and the participants agreed to the term of acceptance approved by the Research Ethics Chamber of the institution.

It started with a semi-structured script:

1. Data: name, age, office and company.
2. How long have you been working with AI/ML?
3. Education and where to study AI/ML?
4. What is the type of product developed?
5. What are the goals and guidelines of the product recommendation system?
6. What is the product development/evolution process? What steps are followed and are profiles participants?
7. How the team/squad you work on is composed? Explore profile proportions and interaction with other teams
8. How to make AI prototypes?
9. What methods are used?
10. Some method has already been abandoned? Why?
11. Does the company follow any list of AI principles?
12. How does the user experience with the product is worked?
13. Do they somehow work on user trust in AI?
14. Efforts are made in Explainable AI?
15. How and at what stages do users participate?
16. What are the difficulties and challenges for UX Designers to work with AI?
17. What is the difference in UX Design`s performance in projects with and without ML?

For the analysis, the interviews were transcribed and then the emerging themes of the answers were organized in an affinity diagram (Martin and Hanington, 2012), grouped in a bottom-up way and identified by colors, according to the Professional Profile. Thus, it was possible to identify and categorize the main issues, contextualized in UX Design practices, involved in the development of ML-based recommender systems.

5. Analysis of interviews

Some objective questions were asked to the participants already in the recruitment form, to assist in the selection. Regarding professional experience, there is a greater concentration of professionals with little experience with AI, up to 3 years, regardless of the profession. This result is understandable by the recent appreciation of AI. Another issue raised was the source of knowledge used by these professionals to work with AI. Few designers acquired any knowledge related to AI in their academic training. Most acquire knowledge in publications, the internet and their daily work. Product managers seek publications and acquire knowledge in their day-to-day work with data scientists. On the other hand, data scientists and developers declare academic knowledge in AI is more present, however, they also consume publications and content about AI on the internet. We note that for these technical profiles, there is knowledge of AI before the work routine. Knowledge in AI is more widespread in technical careers, so it is more natural and valued for professionals of this profile. Overall, the largest reported sources of knowledge were publications and internet content. Perhaps because of the recent appreciation of AI, for those people who are in the market, knowledge was greater in courses than in undergraduate courses.

From the discussions raised in the research, some discoveries were made, based on the reality of the sample:

Professionals interviewed speak of more business objectives than value to people, even if the features are people-oriented. Regardless of the professional profile, the size and branch of the company or the type of product and end-user, when asked about the objectives and guidelines of the recommendation system, more aspects related to the business are noted in the answers. The comments focus, for example, on engagement for customer retention and conversion, rather than people aspects such as meeting human needs. As all the companies interviewed by the interviewees aim at a profit, it is understandable, but it is worth reflecting on how much the user experience with the systems is deprecated or evaluated by simplistic conversion metrics.

The product development processes in the interviewees' companies are often not in line with the vision of the best user experience. Regardless of the size of the company, the practice of Agile methodology for product development is noticeable. Professionals are allocated to teams, called squads, which have specific objectives. This factor makes each squad have the goal of solving a specific problem, losing sight of the user's complete journey with the product. Many interviewees demonstrate a lack of knowledge of the complete process, a lack of interaction with other teams in the company and the lack of vision of how their deliverables are used. For example, a data scientist comments that he knows what data he needs to extract as a result of the algorithm, but he doesn't know what will be done with it. In this way, there is a great appreciation of quantitative data and the algorithm tests are focused on accuracy.

Respondents report difficulties and challenges of currently working with an AI-based recommender system, involving communication between professionals with a technical profile, such as data scientists and developers, and others, such as designers and product managers. In addition to the interdependence of the different profiles and teams participating in product development with AI. They also address the difficulties in the user's view, to understand the minimum operation of the recommendation, necessary for the interaction. Designers and product managers comment on the lack of technical knowledge and lack of literature aimed at a non-technical profile, while technicians focus on process and development difficulties.

In most of the companies interviewed, when there are designers, they work on the value of the product and the experience with the interface, but not with the recommendation system. Only larger companies invest in having designers work on the experience with the products, even so, they are focused on the experience that the user has with the interface, not necessarily on the result of the recommendation. It is rare to find a designer participating in researching the experience that the user has with the recommendation algorithm.

AI is evaluated quantitatively, not qualitatively. When prototypes are produced to be tested with users, the experience they have with the interface is considered. Due to the difficulty of simulating the result of the AI, the prototypes are already made with the real algorithms, or the interface is tested already in the production environment. AI is only evaluated on its accuracy and conversion metrics, not qualitatively. Chen et al. (2019) claim that traditionally accuracy is the main metric to measure the effectiveness of a recommendation system. However, they warn that this can cause the filter-bubble phenomenon, in which users are stuck in a subspace of options that are very similar to their profile and, therefore, lose the opportunity to explore alternatives that may also match their preferences. We conclude that user experience is often investigated superficially or with product metrics. Little goes into the recommendation experience as they expect more active user feedback. In this way, companies can fail to receive a lot of feedback from users, which is important to know their satisfaction with their product and indicate opportunities for improvement.

The same methods are used to evaluate products with and without AI. When a designer is participating, interviews and usability testing are often used to collect qualitative data. The A/B test is also widely used to collect quantitative analysis. No abandoned method was identified because there are AI algorithms in the product.

When interviewees comment on the differences between working on product development with and without ML, they bring up the issue of decisions that were previously defined in the project, now being taken by AI, generating a wide variety of possibilities and unpredictability. They also commented on the dependence on data collection and treatment, in addition to a greater need for tests to validate hypotheses. Some interviewees talk about AI still evolving and having the purpose of increasing human capabilities, so the impacts of what we collect today will still be reflected in the future. One interviewee suggests that every problem solving should be tested first without AI, only after proven AI should be included as an improvement and scalability, adding value to the product.

The proportion of designers participating in the development of recommendation algorithms is reported by respondents to be much lower than that of professionals with a technical profile, such as data scientists and developers. Often, recommendations are defined by teams made up of only data scientists. The user experience designer's profile appears when there is money for investment as if it were not essential, but a differentiator for the product. One interviewee argues that it is difficult for designers to be interested in more technical topics. It is possible that this is a matter of profile and that it contributes to the reduced number of designers in studies with technical bases such as ML.

Designers are not very present in these companies' innovation labs. The design professional participates when a technical solution has already proved to be effective, to work on how to improve the user experience with the product. One interviewee comments that technicians are guided by technology innovations, as a result, products are born guided by technology as well.

When users are involved throughout the product development/evolution stages, they are usually involved in the discovery and/or validation. Often, validation is performed only quantitatively. Users would then be present in the initial stages of product or functionality design and at the end of the process, for validation.

Most companies do not follow any list of AI principles. Only a few ethical principles best known for disclosure are empirically considered. Some respondents who work with AI do not even know any of the lists of principles of interaction with AI published by market, academic, or government institutions such as Google AI Principles (Google PAIR, 2019), Beijing AI Principles (BAAI, 2019), OECD Principles on AI (OECD, 2019) and Recommendation on the ethics of artificial intelligence (UNESCO, 2021). There is an only incentive on the part of the company when there is a possibility of involvement in a legal problem.

The trust that the user has in the recommendation is not a topic much discussed by companies. Some believe that they achieve trust with the good accuracy of the algorithms. Two interviewees comment that user participation in development stages already guarantees trust. Only two demonstrate concern in qualitatively validating the result of the algorithm. In some cases, trust can be a very relevant factor in the acceptance of the recommendation offered by the system.

Some companies work on the explainability of the algorithm, but the black box algorithm model is still more common. It is then noted that the transparency of the recommendation is not yet a priority for these companies. Whether due to technical limitations or not to reveal “the gold” to competitors, as one of the interviewees says.

6. Discussion

In this research, the question of technology driving the development of AI/ML-based recommendation systems for VoD platforms was explored. As Verganti (2011) puts it, technological innovations would be driven by the technology itself and then improvements would be motivated by the perceived needs of the market.

The professionals interviewed point out the guidelines of their products with business objectives. We understand that they are for-profit products, but it demonstrates how the needs of users are not considered paramount factors. There are many comments in the sense that if the product performs well, customers are satisfied. Would it be enough then to evaluate the experience that users have with the recommendation through conversion metrics? If we limit ourselves to that, we only solve problems after they already exist. Qualitative user-focused methods can, in addition to exploring the solution to problems, identify opportunities for the business.

Sometimes there are no users present at any stage of a product's development or evolution. Even when there is no investment to participate users, aiming at a good experience using the recommender system, they are considered in the Discovery stage, for initial research and/or at the end, for validation of the proposed solution. Users could be participating in the intermediate steps, with participatory design and contextual design methods, indicated by Shin et al. (2017), to help with decisions during product maturation. The authors explain that participatory design consists of involving real users in the product design process, while contextual design studies the usage behavior of users in their natural environment. Both methods collect insights from a user-centric view during the product development process. Another factor that may indicate the lack of focus on the user is that the vast majority of companies do not follow any list of AI principles, created to care for human beings in the face of the use of AI. In theory, AI should serve to increase human capabilities, bringing benefits to people. That is why it would be so important to be followed, although they should not be treated as dogmas. Each case must be analyzed in its context for the best decision-making in the construction of the algorithm. If, in many cases, the principles are related in a way that complements each other, in others, there may be conflict. To follow the principle of diversity (UNESCO, 2021), content outside the user's mapped pattern is offered to him, in search of serendipity. On the other hand, this offer must be dosed, as the principle of user assistance (BAAI, 2019) advocates the reduction of information overload, filtering according to the user's profile, to reduce the range of options and direct them to your focus.

Often, the work scenario in which professionals in companies find themselves, also does not contribute to the product being developed with a good user experience. First, we find professionals allocated to a squad, whose focus is on a part of the product. This makes the professionals of this team not have a complete view of the user's journey. Added to this, there are communication problems between different professional, technical and non-technical profiles, reported by the interviewees, who claim that they seem to “not speak the same language”. Yang (2020), in his thesis, also points out collaboration with AI engineers as one of the challenges for designers. The lack of literature on AI-focused non-technical profiles further increases the gap between professionals. Although there are already some books such as Machine Learning for Designers by Patrick Hebron (2016) and articles, the topic of reading is still not easy for designers, nor is the reality of the market. As reported by Yang, Banovic and Zimmerman (2018), there is a lack of research integrating UX and ML, which would be important to envision new ways for ML technology to improve the quality of the user experience. In this context, designers find a great barrier to working on the user experience with an ML-based recommender system.

Generally, in the companies of the interviewees of this research, when designers are participating in the process of developing a recommender system based on AI/ML, the value of the product and the experience that the user has with the interface are worked on, but not with the system of recommendation itself. Products with ML are evaluated using the same methods already common in the market to evaluate products without ML, such as usability testing. As it is difficult to simulate AI and ML depending on the time to learn from the user, user tests are done focusing on screen usability and other functionality. Algorithms, in turn, are evaluated quantitatively, with a mass of data, as ML needs time to learn from the user. In addition, each user can only assess whether a particular recommendation works for them. Yang (2020), in his thesis, points out a challenge faced by designers to work with AI, the understanding of how AI works and its capabilities, in addition to the construction and testing of interactive prototypes with AI, among others. Although products with and without ML are tested by the same methods, they present real differences, mainly because decisions that were previously defined in the project, are now made by AI, generating a wide variety of possibilities and unpredictability. Designers are not used to designing this way. Are new methods possible to assess AI? Or what adaptations would current methods need to undergo to assess AI? We understand that a quantitative method indicates the existence of a problem, but that it is only possible to be explored in depth by a qualitative method. At what stages of development should we evaluate AI with user engagement?

The representation of designers in the process of developing interfaces with a recommender system is very small in the companies of the professionals who were present in our research. In addition to finding few professionals working in the role of designer, if we compare with data scientists and developers, designers are rarely present in the innovation laboratories of these companies. Dove et al. (2017) note a lack of design innovation with ML and a gap between research and its applications in the market. There is therefore a whole way for designers to train themselves and conquer their space in the process of developing products with ML.

All the issues discussed here, about the market and the professionals participating in the development of interfaces with an AI/ML-based recommendation system, impact the user experience with the generated products. As reported by the professionals interviewed, transparency is still not much worked on. This causes users not to form an adequate mental model of how the system works, to maximize the use of its features. Furthermore, as pointed out by Gilpin et al. (2019), the lack of transparency implies the reduction of users' trust in what is recommended by the system. We therefore defend that the lack of transparency of VoD platforms is one of the main problems to be solved to improve the experience of its users.

7. Conclusion

Historically, technology develops from the perspective of technology itself, not from a human-centered view. Innovations would come from the willingness of technologists to prove the capabilities of new technologies. Along these lines, the use of ML seems to have been driven by data availability and technological advances, not user need. UX designers participate at a later stage, to improve the experience of using a product, at the very least, already conceived. Designers still face several challenges when working with ML, such as: having to learn to design with the unpredictability of ML and the lack of training.

This research demonstrated the unrepresentative role of the UX designer in the development of recommender systems based on AI/ML, difficulties in communicating with data scientists and insufficient methods to evaluate the algorithm qualitatively, with a focus on the user. We defend that to ensure a good user experience, the product's focus needs to be on its users. The user experience is fundamental for user engagement with VoD platforms, in line with other issues such as collection, value, etc. Therefore, companies need to invest in qualitative data to evaluate algorithms and have professionals concerned with the complete journey of using the recommender system. In addition, user focus must exist at all stages of the product design process, from ideation, through development, algorithm modeling, validations and following with continuous discovery, for product maintenance and evolution. As developers and data scientists do not necessarily have UX training, UX designers should participate at every step. There should also be an incentive to bring users whenever possible, with participatory design and contextual design methods throughout the process, in addition to the usual surveys and validations. One cannot forget that it is necessary to train design professionals to work with AI/ML.

AI is new and keeps pace with the rapid evolution of technology. Recommendation systems based on AI/ML are used to add value to products, as their differential is to filter content in a personalized way, saving the user's time. In this sense, the user is somehow placed in the role of designer, as AI reacts to their actions and offers a personalized solution, with countless possibilities and unpredictability. For this, professionals need to learn metrics and technical concepts to work on the development of interfaces based on AI/ML, but they cannot forget about human factors. As commented by one interviewee, “the metrics may make sense for the model (algorithm) but not for the business”. People's behavior changes over time and is influenced by context. That's why we need professionals constantly evaluating the user's experience with the product, to ensure that their needs are met. On the other hand, it is necessary to train UX Design professionals, generate content on the topic of AI/ML aimed at this profile and work on the business culture.

In future developments, we have room to investigate how to foster user focus and designers' representation in AI/ML-based recommender systems development processes. Furthermore, we highlight the importance of proposing and testing new methods to evaluate the user experience with these systems, respecting the particularities of ML.

8. Referências Bibliográficas

AGGARWAL, C. C. **Recommender Systems: The Textbook**. Yorktown Heights: Springer International Publishing, 2016.

BAAI. Beijing AI Principles. 2019. Disponível em: <https://www.baai.ac.cn/news/beijing-ai-principles-en.html>. Lats acess: Oct 15, 2021.

BARBOSA, S. D. J. et al. **Interação Humano-Computador e Experiência do Usuário**. Self-publishing, 2021.

BODEGRAVEN, J. VAN. How Anticipatory Design Will Challenge Our Relationship with Technology. **AAAI Spring Symposium - Technical Report**, 2017. v. SS-17-01-, p. 435–438.

BUDIU, R. Can Users Control and Understand a UI Driven by Machine Learning? 2018. Disponível em: <https://www.nngroup.com/articles/machine-learning-ux/>. Last acess: Nov 22, 2020.

CHEN, L. et al. **How serendipity improves user satisfaction with recommendations? A large-scale user evaluation**. The Web Conference 2019 - Proceedings of the World Wide Web Conference, WWW 2019. **Anais**...Association for Computing Machinery, Inc, May 13, 2019.

CRAMER, H.; THORN, J. Not-So-Autonomous, Very Human Decisions in Machine Learning: Questions when Designing for ML. **AAAI Spring Symposium - Technical Report**, 2017. v. SS-17-01-, p. 412–414.

DOVE, G. et al. UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. **Conference on Human Factors in Computing Systems - Proceedings**, 2017. v. 2017- May, p. 278–288.

ENDSLEY, M. R.; JONES, D. G. **Designing for Situation Awareness: An Approach to User-Centered Design**. second ed. Boca Raton: CRC Press, 2004.

GILPIN, L. H. et al. Explaining explanations: An overview of interpretability of machine learning. **Proceedings – 2018 IEEE 5th International Conference on Data Science and Advanced Analytics, DSAA 2018**, 2019. P. 80–89.

GILPIN, L. H. *et al.* Explaining explanations: An overview of interpretability of machine learning. **Proceedings – 2018 IEEE 5th International Conference on Data Science and Advanced Analytics, DSAA 2018**, 2019. P. 80–89.

GOOGLE PAIR. People + AI Guidebook. 2019. Disponível em: <pair.withgoogle.com/guidebook>. Last accessed: May 7, 2020.

GUEST, G.; BUNCE, A.; JOHNSON, L. How Many Interviews Are Enough? Field Methods, v. 18, n. 1, p. 59–82, 21 fev. 2006. Disponível em: http://journals.sagepub.com/doi/10.1177/1525822X05279903

HEBRON, P. **Machine Learning for Designers.** 1. ed. Sebastopol: O'Reilly Media, Inc., 2016. v. 1

HOLZINGER, A. From machine learning to explainable AI. **DISA 2018 - IEEE World Symposium on Digital Intelligence for Systems and Machines, Proceedings**, 2018. n. August 2018, p. 55–66.

KONSTAN, J. A.; RIEDL, J. Recommender Systems: From Algorithms to User Experience. **User Modeling and User-Adapted Interaction**, 2012. V. 22, n. 1–2, p. 101–123.

MARTIN, B.; HANINGTON, B. **Universal Methods of Design: 100 Ways to Research Complex Problems, Develop Innovative Ideas, and Design Effective Solutions.** Beverly: Rockport Publishers, 2012.

NORMAN, D. A.; VERGANTI, R. Incremental, and Radical Innovation: Design Research vs. Technology and Meaning Change. **Design Issues**, 2014. v. 30, n. 1, p. 78–96.

OECD COUNCIL RECOMMENDATION ON ARTIFICIAL INTELLIGENCE. OECD Principles on AI. 2019. Disponível em: <https://www.oecd.org/going-digital/ai/principles/>. Last accessed: Oct 15, 2021.

ROUHIAINEN, L. **Artificial Intelligence: 101 Things You Must Know Today About Our Future.** [S.l.]: [s.n.], 2018.

SHIN, Y. et al. Design for experience innovation: understanding user experience in new product development. **Behaviour & Information Technology**, v. 36, n. 12, p. 1218–1234, 2 Dez. 2017.

SPRINGER, A.; HOLLIS, V.; WHITTAKER, S. Dice in the Black Box: User Experiences with an Inscrutable Algorithm. **AAAI Spring Symposium - Technical Report**, 2017. v. SS-17-01-, p. 427–430.

UNESCO. **Recommendation on the ethics of artificial intelligence.** 2021

VERGANTI, R. Radical Design and Technology Epiphanies: A New Focus for Research on Design Management. **Journal of Product Innovation Management**, 2011. v. 28, n. 3, p. 384–388.

VERGANTI, R.; VENDRAMINELLI, L.; IANSITI, M. Innovation, and Design in the Age of Artificial Intelligence. **Journal of Product Innovation Management**, 2020. v. 37, n. 3, p. 212–227.

YANG, Q. Proofing **Artificial Intelligence as a Material for User Experience Design.** 2020. Tese (Doutorado em Ciência da Computação) – Human-Computer Interaction Institute, Carnegie Mellon University, Pittsburgh.

YANG, Q. The Role of Design in Creating Machine-Learning-Enhanced User Experience. **AAAI Spring Symposium - Technical Report**, 2017. v. SS-17-01-, p. 406–411.

YANG, Q.; BANOVIC, N.; ZIMMERMAN, J. **Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Innovation.** Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. Anais...New York, NY, USA: ACM, Apr 19, 2018.

Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.