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User Experience Design Using Machine Learning: A Systematic Review

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ABSTRACT User experience (UX) is the key to increased productivity by enhancing the usability and interactivity of the product. Machine learning (ML) solutions have raised user and academic awareness of technical innovation. As a result, ML is becoming increasingly popular to improve the quality of UX. Several investigations have highlighted a potential lack of studies on the overall challenges and recommendations for UX using ML. Therefore, more attention should be paid to ML's existence and potential applications across various applications to get the most out of ML techniques to improve the UX design process. To this objective, a systematic review of the literature was performed as to determine the challenges faced by UX designers when incorporating ML in their design process. Recommendations that help UX designers incorporate ML into UX design will be highlighted. Furthermore, the PRISMA approach is used (a process that has been established in the literature), to restrict the chance of bias at the selection stage. Relevant articles in the following four databases were searched: IEEE Xplore, Scopus, Web of Science, and ACM. The findings revealed that the number of publications on issues linked to UX with ML had advanced exponentially. This review highlights the challenges, recommendations, tools, algorithms, techniques and datasets used in different studies. In addition, suggestions are given for future investigations.

INDEX TERMS User experience, experience design, UX, ED, machine learning, ML, HCI, UX design, user interaction, user behavior.

I. INTRODUCTION

Over the last few decades, user experience (UX) and machine learning (ML) are relatively new topics that have made significant progress in website designs. As these two disciplines grow more relevant and become widely used throughout industries and applications, they open a multitude of research opportunities. Within the realm of human-computer interaction (HCI), UX is considered a critical factor to developing successful, efficient and pleasant solutions. The use of ML to improve UX is becoming more common [1], [2]. Conversion rates in applications with excellent UX design can increase by 400 per cent, whereas conversion rates in applications with inadequate user interfaces (UI) only increase by 200 per cent [3].

As for ML, researchers and digital designers recognize that the ML trend has become especially interesting since it opens many new design opportunities for UX designers [4], [5]. The authors of [6], viewed ML as the new UX. Even though ML has demonstrated its ability to enhance the UX in today's services and products, researchers suggest that the UX design practice underpins complex challenges when using UX as a design material (e.g., [7], [8], [9]).

L. M. Policarpo *et al.* [6] gave an overview of the obstacles UX designers face when using ML as a design element. One example of the obstacles is the struggle UX designers go through when collaborating with data scientists in a proactive manner. Another obstacle is the lack of the tools and abilities needed to sketch or prototype when using ML as a design material. It is implied that existing UX design education and practice are unprepared to work with ML as a design resource [10]. For example, UX designers may find ML too technically challenging design material [11], and therefore they may decide to shift the current design process due to their unawareness of design tools and methodologies to verify the viability of ML-powered solutions. As UX designers in [8] surveyed their experiences working with ML, they claimed their obstacles. In particular, they were worried when developing something ethical and purposeful. Even though ML is predicted to bring concrete benefits to designers, it is not clear

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how to incorporate it into design processes [8], resulting in untapped potential [8].

Technology-assisted creativity, such as Simon's optimization-based design [12], Tiedemann's "creativity support tools," [13], and Horvitz's "mixed-initiative user interface," [14] can all be linked to today's interest in employing ML in order to assist human creativity. Recent related research presents some inspiring illustrations of ML-based UX design tools. For example, such tools can use formal models to optimize graphical user interface (GUI) layouts in order to meet objective performance criteria [15].

An ML automatically vectorizes existing digital GUI designs (using computer vision) to quickly transfer them to new projects [16]. It also enables quantifiable evaluations of given GUIs by utilizing a set of user perception and attention models [17]. Furthermore, Chen *et al.* [18] recently used deep learning to translate digital user interface (UI) mockups into UI specifications (e.g., Android layout XML). Infrequent design tools assist the automated shift from paper to digital material: Microsoft [19] and Airbnb [20] are experimenting with converting paper sketches directly into GUI code, bypassing much of the digital wireframing phase. They also claim that UX designers' difficulties when dealing with ML limit their ability to innovate and think outside the box.

There has been continuing study on how to approach UX design practice while working with ML as a design material ([8], [10], [21]). According to [22], ML "will force us to rethink, restructure, and reassess what is feasible in practically every experience we create". [10] warned, designers will not be able to fully exploit ML's strong potential if they do not understand the technical side of the technology, which involves statistics, data analysis, and programming in the first place. Secondly, dealing with ML as a design material is like the last challenge in that a lack of awareness of ML's full potential can lead to setbacks in employing it as a design material.

Despite ML's growing importance in the field of UX design, several recent studies have found that many UX designers are unaware of its possibilities and limits ([5], [23], [10]). The main reason for this lack of knowledge is that current models of UX design learning fail to suitably inspire design learners to work with ML [8].

A wide range of products and services, particularly in the digital sphere, employ ML in various crucial ways. One of the most sought-after and valuable applications of ML in UX design is its capacity to provide users with new levels of personalization. L. M. Policarpo *et al.* [6] described ML as an untapped possibility for UX designers and that it has yet to be fully realized as a design material. Algorithms that learn from underlying data sources are frequently used to improve UX [7].

This review aimed to systemically report UX designers' challenges during incorporating ML in UX design. In addition, this review presents an evaluation of the effectiveness of the available written approach in enhancing the UX using ML. The structure of this review paper is organized as follows; the next section, Section II, describes our methods for locating academic and non-academic materials, emphasizing the need of avoiding bias. Section III is the results section where we present our findings and their categorization. Discussion and analysis of the results is presented in Section IV. Limitations of the findings are discussed in Section V. Suggestions for future research as some research gaps are identified are shown in Section VI. The conclusion is given in the last section, Section VII where we state implications of our findings.

II. METHODOLOGY

This research was motivated by the following three research questions: RQ1 - 'What are the challenges facing UX designers while incorporating ML algorithms of UX design?', RQ2 - 'What are the recommendations for how ML's functionality can be incorporated into the UX design process?'. Finally, RQ3 – 'How can ML's algorithms be used to help make better UX design decisions?'. We looked at contemporary literature as a critical source of answers to these study questions in order to completely achieve the research objectives.

A. RELATED STUDIES SEARCH METHOD

First, in early October 2021, we searched electronic databases the Web of Science (WoS), Scopus, IEEE Xplore, and ACM. We chose the mentioned database previously since it aids as the entry point for all Computer Science and Social and Behavior Science [24]. Then, we designed a search string using our understanding and knowledge of the UX design and ML domains and consulting relevant UX design and ML search strings. Table 1 shows the search string for all databases.

B. STUDY SELECTION

The articles that were discovered during the search were saved in Microsoft Excel. Duplicates and relevance to the study title were checked against the article list. Any publications that were not related to UX and ML were rejected. The titles and abstracts of all full-text articles retrieved were examined by two researchers (AMA and KIG) to exclude those that were unrelated to the research topic. If the two researchers differed on the papers' relevance, they would discuss it with the third reviewer (TCY).

The chosen studies were divided into two categories: Screening was completed first to reject articles based on title, keyword, and abstract modifications, followed by a full-text evaluation. The query's results that had nothing to do with UX or ML, such as coincidences with other UI and UCD that weren't part of the "User Interface" or "UI" concept, were also removed.

C. CONDUCTING THE REVIEW

In the end of January 2022, the systematic literature review detailed in this paper was completed. We have performed a comprehensive text review of each of the 18 articles listed in Figure. 1. For systematic reviews, we adopted the PRISMA statement, which was introduced in [25]. The PRISMA diagram for this review is shown in Figure 1.

D. IDENTIFICATION

The following databases were searched: IEEE Xplore, WoS, ACM Digital Library, and Scopus. The search engines of the four libraries were configured to execute search queries both in the metadata and in the full text of articles. A filter was added to the questions to ensure that the results did not include any articles released before 2017, the year in which the first study utilizing machine learning in user experience was published.

The IEEE, WoS, ACM, and Scopus now have a second filter that excludes articles authored in languages other than English. Articles in other languages were manually eliminated throughout the screening process in the other libraries. As illustrated in the upper level of the PRISMA diagram in Figure 1, this query returned 1,044 publications from the four digital libraries.

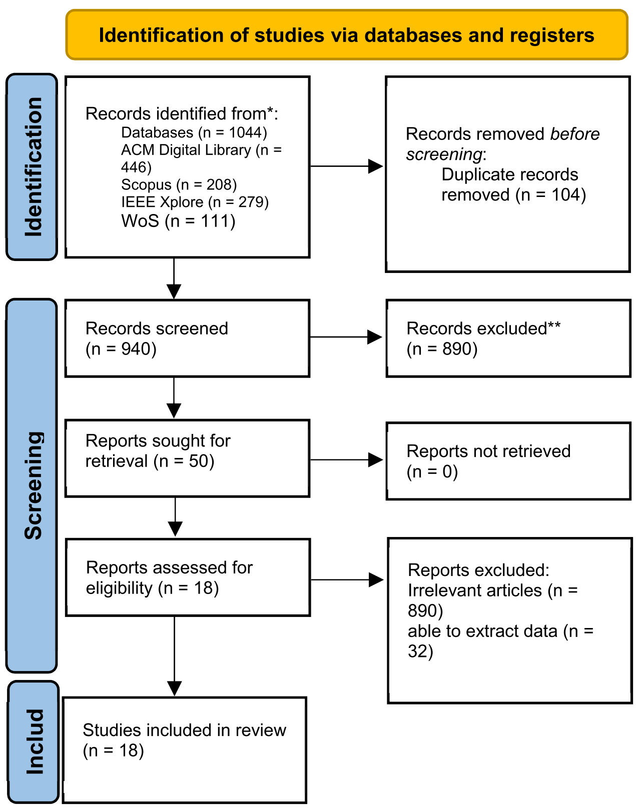

FIGURE 1. **PRISMA flow diagram for this systematic literature review.**

TABLE 1. **Search string for databases.**

Source	Search String	Filters
WoS	TS=(("User Experience" OR "UX") AND ("Machine learning" OR "ML"))	Web of Science Categories: Computer Science Artificial Intelligence or Computer Science Information Systems or Computer Science Theory Methods or Computer Science Software Engineering or Social Issues or Behavioral Sciences Document Types: Articles Language: English Research Area: Computer Science Year: 2017 – 2022
Scopus	TITLE-ABS-KEY ("User Experience" OR "UX") AND TITLE-ABS-KEY ("Machine learning" OR "ML")	Publication Stage: final Document Types: Articles Subject Area: Social Sciences and Computer Science Language: English Publish Year: 2017, 2018, 2019, 2020, and 2021
IEEE Xplore	("All Metadata":"User Experience" OR "All Metadata":UX) AND ("All Metadata":"Machin e Learning" OR "All Metadata":ML)	Document Types: Journals and Early Access Articles, Conferences Year: 2017 - 2022
ACM	Abstract:(("user experience" OR UX) AND ("Machine learning" OR ML)) OR {Publication Title:("User Experience" OR UX) AND ("Machine Learning" OR ML)}	Publication type: Journals, Article Type: Research Article, Publication Date: (01/01/2017 TO 12/31/2021), ACM Content: DL

E. SCREENING

One hundred four articles were initially removed from the original 1,044 because they were found in multiple libraries. The screening procedure then began, with one of the researchers going over the title, abstract, and keywords of each of the 1,044 publications. Those papers for which the library did not give the entire text and results from textbooks were excluded from this review.

The results of the query that had nothing to do with UX and ML were also deleted, including, for example, coincidences with other Usability and UX Evaluation concepts. In total, 922 results were eliminated in this screening, none of which were subjected to a full-text examination. There were 18 papers for full-text review currently. As a result of this phase, 922 articles were rejected, leaving only 18 for the qualitative synthesis.

F. ELIGIBILITY

We evaluated the 18 publications for eligibility. According to the criteria outlined in Section B Study Selection, the researchers discarded a set of papers. A cross-review of the discarded documents was performed to ensure no contradictions. The researchers also pitched some publications that were irrelevant to UX design using machine learning.

These are works that propose educational tools using machine learning, for example [26]. In addition, the study by [27], calculates this number in linear time to find a number that summarizes all interactions between an object and a user.

G. INCLUDED

As can be seen in the lower portion of Figure 1, the study comprised a total of 18 articles that applied machine learning in UX design and so answered the research question. A researcher conducted a cross-review of this list, and the discrepancies discovered were resolved. Table 2 summarizes the papers reviewed and included in each review step, organized by the digital library to which they belong, year of publication, and citation count.

TABLE 2. Summary of reviewed papers.

Database	Published Year	Source	Citation count
WoS	2017	[8]	238
IEEE	2017	[28]	75
WoS	2018	[10]	115
ACM	2018	[7]	68
ACM	2019	[29]	2
ACM	2019	[30]	9
Scopus	2020	[31]	44
IEEE	2020	[32]	2
ACM	2020	[33]	13
ACM	2020	[34]	3
Scopus	2020	[35]	1
ACM	2020	[36]	1
IEEE	2020	[26]	0
ACM	2020	[5]	107
Scopus	2021	[37]	0
Scopus	2021	[38]	1
Scopus	2021	[39]	4
WoS	2021	[40]	0

III. RESULTS

A. CHARACTERIZATION OF THE RESULTS

The results of full-text research of the collected articles are shown in this section, organized by the analyzed topic. We analyze the reports in three main categories: surveys and interviews, tools, and datasets.

1) GENERAL CHARACTERISTICS OF RQ1

Based on the findings of the associated articles for challenging facing UX designers during incorporating ML. Designers admitted that they had a limited understanding of how ML worked and was not a priority. Instead, they used designer abstractions and well-known exemplars to describe ML and convey design ideas among themselves. The most effective strategy to help designers connect with ML as a design material is to tell them how it works. ML projects take longer to plan and execute than other design projects. In addition, designers worked closely with data scientists to solve their problems; they did not hand over fully developed designs to a technical team. Instead of providing abstractions, exemplars, and new tools and methods to support collaborating with data scientists, a new way to inspire will benefit UX designers using ML.

Comprehending the limitations of what an ML system can learn, experimenting with different formulations of an ML problem, and assessing the performance of ML models in the context of their unique application are formed the challenges facing UX designers. Translating real-world problems into learnable tasks, optimizing the design of the ML model rather than aiming to enhance performance by adding more training data, evaluating model performance, and correcting for bias and overfitting are all challenges in this area. The stated issues have a lot of overlap, with all of them relating to understanding ML capabilities and mapping them to practical applications and the capacity to analyze how well a trained model performs in a particular setting.

Explicitly addressing the issues that UX designers face, instead of being considered throughout the process, UX is frequently an afterthought. Available data limits UX ideas, and designers struggle to collaborate with data scientists proactively. It's challenging to prototype ML, and it doesn't play well with designers' "fail early, often fail" strategy. Designers have a hard time grasping the capabilities of ML in the context of UX. Several issues are related to development methods and communication in mixed project teams. Others are more basic, highlighting a mismatch between ML as a design material and the context in which they were found. The results of our review summarize the challenges faced by UX designers; hence, we assume that the best fits of each challenge faced by the UX designers provided as shown in Table 3.

According to [33] introduce an approach that suggests user experience (UX) is an interactive ML, which the term IML refers to ML applications that rely on ongoing user engagement. Some surveys to learn more about each participant and understand if they have ever been participated in ML practices and design [8]. Dove *et al.* (2017) investigated how to make UX design and ML experts collaborate. At the same time, the study by [34] identifying interesting directions for the application of ML to UX. As [36] points out involves the iterative generation of design artefacts and experiential ways that assist designers in the growth of their knowledge abilities through applying concepts with ML. How do UX practitioners predict the synergies between UX work and ML techniques? The authors conducted 13 semi-structured interviews with UX experts. In addition, surveyed 49 practitioners experienced in UX, ML. [36] claimed that most respondents believe that ML and UX will become increasingly intertwined in the future. Also, the authors mentioned that 13 respondents currently see the minimal overlap. In addition, eight respondents expect the overlap to increase in the future. Respondents were asked to evaluate their present perceptions of the relationship between ML and UX. As well as how they believe it will change in the future. Only nine respondents believe ML and UX intersect to some or a significant amount in the current situation. However, 23 believe that ML and UX will converge to some extent in the future. In total, 35 of the 49 survey respondents believe that the interaction between the two disciplines will grow in the future. In addition, [34] interviewed 13 UX experts from industry and academia in semi-structured interviews to learn how they envision ML technologies enhancing or influencing their UX processes.

The authors pointed out that many participants, so unsupervised ML has a lot of potential in user segmentation. For example, data logs can automatically identify unique user groups using clustering approaches. Another area of focus was assisting design decisions by analyzing and recommending UI solutions based on previous user behavior or preferences [36]. While [34] proposed term is called Interaction Design. Interaction Design develops mappings between factors of UX and those of IML, which contains four elements that influence UX (Artifact, context, epistemology, and collaboration).

TABLE 3. Summary of challenges faced by the UX designers.

Challenges	Source
Consider how ML statistical intelligence interacts with human common-sense intelligence.	[10], [35]
Consider how you could use ML in less obvious ways.	[10], [35]
In early prototypes, represent ML's reliance on data.	[10], [35]
Prioritize ML's ethical considerations.	[8], [10], [33]
ML technical capabilities still understood.	[8], [10], [34], [35]
Improvements in the design process that appear to be directly related to using ML	[8], [10], [35]
Recognition of a data science culture by UX designer participants is still missing.	[10], [36], [35]
Changing Roles and Expectations.	[36], [35]
Access Users' Information / Data	[10], [35]
Developing appropriate environments and tools to aid designers' research and hands-on interaction with ML	[10], [36], [35]
Allowing designers to reflect on their experiences with these environments and technologies to enhance their experiential learning.	[10], [36], [35]
Assisting designers in encoding their conceptual and operational understanding of ML into their designs to improve the end-user experience of training and customizing applications.	[8], [10], [36]

2) GENERAL CHARACTERISTICS OF RQ2

Many recommendations draw the path to incorporate ML into the UX design process. For example, integrate UX designers with data science engineers to develop ideas, creative experience, and inspirational content for designing a product or service using ML capabilities. In addition, UX and HCI instructors originate more ML-related courses geared to attract UX designers from various disciplines. For examples, techniques that demand collaboration between UX designers, data scientists, and software engineers.

This collaborative, creative approach would be beneficial to UX designers. The discussion between UX designers and data scientists was centered on determining a design goal that was worthwhile to pursue. Our findings revealed many recommendations to incorporate ML functionality into the UX design process, as illustrated in Table 4.

TABLE 4. Summary of recommendations.

Recommendations	Source
The UX designer must collaborated with data scientists	[8], [10]
Integrate ML techniques into the UX design	[8], [35]
Supporting design decisions based on historical data of user behavior or user preferences.	[10], [35], [36]
ML approaches may provide a more cost-effective solution for improving UX design	[8], [10], [35], [36]
Building ML tools for the UX design process based on interactive ML principles	[35], [36]
Implement educational materials include case studies, practical workshops, programs, and conferences on how to apply ML to UX design process	[8], [10], [35], [34], [36]

[8] claim that the UX designer needs to collaborate with data scientists. When using ML techniques with the help of tools and processes, UX designers should respect and comprehend the complexity and richness of a design issue. Because it is vital to specify the design criteria, UX designers should know what tools and procedures to utilize to integrate ML techniques into the UX design [8], [10].

For example, to satisfy a commercial value or achieve the users' aim. Therefore, a UX designer's use of ML techniques during the design process can substantially impact the UX [35]. A UX designer's profession and education entail using ML algorithms to investigate links between various design solutions, including different design materials [34].

According to [36], design practice is always unique in some way, whether in a new context, the type of historical data of user behavior, or user preferences. ML's ability to empower the UX in today's more cost-effective option for boosting UX design [35]. Furthermore, other researchers claim that a new understanding of ML techniques in organizational and procedural contexts can significantly impact the UX design process [10], [35].

[7] recommend that UX and HCI teachers develop more ML-related courses to attract cross-disciplinary UX designers. For example, methods demand collaboration between users, designers, data scientists, and software engineers. This collaborative, creative approach might be beneficial to UX designers.

3) GENERAL CHARACTERISTICS OF RQ3

Incorporating ML algorithms and techniques with UX design are still misunderstood due to the complications of UX design using ML and lack of studies. We are increasingly noticing a shift from experiences 'powered by 'ML' to ML as the experience itself in the previous years. Understanding how and what ML models do can help us approach design thinking for ML in new and creative ways to help UX designers. We must consider ML as a cultural and historical artifact, both the labelled data entering the model and the predictions that result.

How can UX designers take advantage of their unique ML capabilities while changing their process design over time? According to [37] that current UX and ML algorithms can forecast final user satisfaction, which is essential for users' decisions about further use or whether they recommend a product or service to others or not. [37] reveal that the ML process can help predict last user satisfaction in at least two contexts: Experiment I, service usage, and Experiment II, product usage [37].

[41] reveal that the BN method is valuable for creating and manipulating probabilistic models for dealing with uncertainty in context-aware systems. [38] proposed Bayesian UM uses contextual data to identify four degrees of accurate, original, diversified, and popular publications for users [38]. In addition, [38] suggest in their research the parameters were computed by employing the bn.fit function using bnlearn package, which operates the network data to evaluate their highest likelihood.

Therefore, this study seeks to provide a UX model that uses the Bayesian network (BN) method to recognize the most relevant contextual data to make appropriate paper recommendations for scholars [38]. While the study by [40] argue that a forward feature selection technique was used to find the optimal collection of features for each type of model.

A program that uses ML techniques to detect users' emotions using user interaction data from websites is demonstrated. It has a lot of promise: the predictive models outlined can be readily included in a script that web developers may use to record users' interactions with a web page and infer their emotions [40].

[31] designed a novel framework to evaluate the business value of a coupon targeting model to enhance UX. The authors adjust classification models utilizing random search and 10-fold cross-validation [31]. Furthermore, cross-validation for benchmark models ensures that all page views relating to a user session appear in the same fold and preserve their original order. Avoid scenarios where earlier page views of a user session show up in the holdout fold, but later page views are used for training [31].

B. QUESTIONNAIRE AND SURVEYS

This section reviews and summarizes the survey questions used in the questionnaires. Table 5 summarizes the questions for the UX designers' backgrounds of using ML capabilities.

TABLE 5. Summary of survey questions.

Questions	Items	Source
Experience in designing ML applications	Have you ever designed an application that uses ML?	[8], [35]
Self-rated skill levels in design and programming	How would you rate your design skills? How would you rate your programming skills?	[8], [35], [36]
Understanding of the performance of various ML capabilities.	Recognize emotions from faces Recognize age from faces Recognize gender from faces Recognize generic objects Recognize specific objects or gestures Recognize human body pose Generate images of fictitious objects or scenes Generate images of fictitious faces Generate music in a particular style Translate text into a particular style Translate images into a particular style Remove things from images	[35]
Self-reported awareness and understanding of various machine learning aspects	ML systems need to be trained before beginning useful How the quality and quantity of training data affects ML performance Assessing the quality of training data Assessing how much training data is needed Assessing the accuracy of a ML system Interpreting uncertainty in ML predictions Identifying bias in ML predictions Understanding possible sources of bias in ML	[8], [10], [35]

C. TOOLS

ML is not yet systematically integrated into design patterns, design education, or prototyping tools. In this section, we review prototyping tools that incorporated. The prevalence of the designers represented that working with ML as a design material. New methods and tools are needed to understand the work with ML effectively. For example, we sketched ideas concerning ML as a design material during the UX design process.

At the same time, the lack of competency demonstrates that most UX designers do not have the necessary knowledge or tools to operate with ML. The existing design process may alter due to the lack of design tools and methodologies to verify the viability of ML-powered solutions, as ML is too technically knowledge-demanding design material for UX designers. The following Table 6 reviewed the related tools drawn by different articles. [39] claim a separate step; participants draw ideas for a design challenge for roughly three minutes. Second, each participant is given one minute to offer their opinion to the group.

This procedure is done three to four times to allow participants to build on each other's ideas and iterate on the

TABLE 6. Summary of ML tools.

Tools Name	Description	N	Source
Paper2Wire	The concept and prototype authors went from a paper sketch to a digital wireframe: (a) A designer draws a user interface on paper, (b) photographs it, and then (c) imports it into wireframing software (Sketch) for (d) further modification. Reflect on lessons learned from this example case for designing ML tools in a user-centered manner that respects practitioners' requirements and practices rather than opportunistically.	20	[39]
ML-Process Canvas	Canvas I and Canvas II are the two parts of the ML-Process Canvas. Canvas I connect the individual UX challenges produced by machine learning to the entire ML process, reminding designers of the issues they need to address at various phases of the ML process. While Canvas II leads designers through the organization and analysis of critical data linked to UX concerns in the ML process.	Prototyping (M: 17, F: 13) Evaluation (M: 11, F: 21)	[29]

designs. As a trade-off between swiftly prototyping an ML-based application and precise predictions, the authors picked Microsoft Custom Vision 9, an established ML platform [39].

This platform was used to develop and test a model for detecting GUI elements in photographs of paper sketches. Microsoft Custom Vision already comes with a high-quality foundation model trained on a large amount of generic image data. The authors generated a series of photographs of GUI drawings and manual labels for further instruction for our specific instance.

The Sketch plugin called this model to detect GUI element kinds and positions. Then the digital wireframe is generated by detecting the relevant GUI components in Sketch Finally, the study's overall design was like that of the pre-study. The authors adopted a within-subject strategy (manual vs Paper2Wire). Qualitative/subjective metrics to acquire comprehensive insights into the concept's potential integration in a practical setting focus on the practitioner's UX.

In comparison, the study by [29] demonstrates that designers can use the ML-Process Canvas to gather essential data throughout the ML process without changing their usual design activities. The tool highlights the individual UX challenges created by ML and then describes the user, scenario, and ML system elements that may affect those UX challenges. In the conceptual phase of UX design, Canvas allows UX designers to organize and show their findings linked to those elements to discover future design opportunities. However, because the current ML system cannot promise that the outputs are always right, the ML system's reactions are designed to be inconspicuous.

TABLE 7. Summary of precise ML-related UX concerns.

Themes	Description	Source
Unpredictability	The problem of dealing with ML systems' unanticipated conclusions based on provided data, regardless of how thoroughly they are trained.	[8], [10]
Transparency	The problem of creating a product whose workings no one can fully comprehend. What effect does this have on system attributes like trust and confidence?	[8], [36]
Learning	The problem is building ML systems that allow user co-control to collaborate with the ML system in decision-making.	[35]
Control	The problem is building ML systems that allow user co-control to collaborate with the ML system in decision-making.	[34], [35]
Anthropomorphism	The problem of deciding the degree of anthropomorphism that can influence how humans view intelligent systems, such as perceived task appropriateness, interaction with agents, and attractiveness	[42]
Interactivity	Supporting the interplay between user feedback and newly learned ML models is problematic. Many ML models are designed to enhance accuracy, but they may not operate fast enough for real-time interaction.	[29], [36]

Therefore, another issue while dealing with ML is establishing tools and approaches. For example, [12] emphasizes the difficulties of sketching or prototyping with massive datasets and the need for computational power, time, and reliance on data scientists [43]. After our restructuring and merging review process, we obtained six groups, each describing one of the typical difficulties illustrated in Table 6.

Each issue has several related themes. Transparency, for example, raises various topics, including explainable AI [43]. In addition, the lack of prototyping using real datasets or including datasets at any phase of process design. Next section, we present the articles that used datasets in their research.

D. DATASETS

1) METHODS OF DATA COLLECTION

Predicting user behavior momentary UX data and ML techniques is a solution for using datasets. This section presents the articles that use datasets in their work. The paper we summarize shows more than methods to build a dataset from a questionnaire, sessions, pageview, and collecting users' data in a period.

Table 8 display the methods of collecting data from different sources. According to Table 8, there are four methods for creating datasets using ML algorithms to enhance UX design. [37] applied two experiments with two sample sizes to check final user satisfaction. In addition, [44] describe the number of samples per class for small which specific algorithms. Some studies have shown that using a smaller sample size for building a classic machine learning model improves performance.

[45] used sampling method is accepted from designing new data or a current original dataset and is used to create a new classification model using ML methods. [32] reveal that a video camera or a webcam continuously captured use face images of each user while they were utilizing products or services, and the data were collected.

TABLE 8. Summary of methods for data collections.

Methods	Description	Sample Size	Source
Survey	Two experiments: First experiment: Fifty healthy university students aged 21 to 24 years were recruited as participants. Second experiment: Twenty-five university students aged 21–24 years were recruited as participants	50 25	[37]
Video Capture	72 videos captured for facial expressions was chunks to 1 minute video. Then System analyzed the captured videos as 72 facial expressions to numeric data.	72 Video	[32]
Survey	The data collection survey lasted 1.5 years and resulted in the collection of 1121 records.	1053 records	[38]
Log Data	Installing plugin in the browser for 30 days. The plugin records, every 2 s, a photo from the webcam that frames the users face in addition to mouse and keyboard logs	527853 objects characterized by 549 features	[40]
User Sessions	Installing plugin in the browser for 30 days. The plugin records, every 2 s, a photo from the webcam that frames the users face in addition to mouse and keyboard logs	556663 sessions 13885 pageview	[31]

In addition, the user's gender and age are gathered. After using the items or services, the user reviews them on a 5-point scale (1 to 5 stars) to determine final user satisfaction. The classification model was validated using leave-one-out cross-validation during the development process. While [38] prepare a suitable dataset for the BN modelling. A web-based application was created to collect the data. A large-scale questionnaire survey was used to collect data for the study.

Participants should have prior expertise working with the Web of Science (WoS) bibliographic database and a minimum of 30 minutes to complete the survey. The researchers were requested to use the WoS bibliographic database to conduct relevant publications for their present work in a naturalistic setting. The participants were asked to provide their current contexts/situations, such as task and pre-knowledge, in Step 1 of the data collection process. Step 2 required the scholars to choose the most relevant paper to their present needs and score it on a 5-point Likert scale for innovation, correctness, popularity, and diversity. Finally, participants had to submit or upload their paper ID (identity paper created in WOS) [38].

[31] collected data is provided by a shop that specializes in selling fashion items and wishes to remain anonymous. The following preprocessing steps are used to prepare the data for analysis. The dataset includes five sessions totaling over 400 page views. Then, due to the significant number of page views indicates that the sessions were produced by bots, remove them from the data collection.

According to [40], a total of 12 participation volunteers of various ages (mean age 32.3) and genders were recruited (6 women). They were requested to install a plugin we created for 30 days on their browser (Chrome or Firefox was necessary). This plugin takes a photo of the user's face from the webcam every 2 seconds and mouse and keyboard logs. A dataset of user emotions and interactions from real users who interacted with genuine websites "in the wild" for 30 days is created. Second, the findings of comparing four commonly employed machine-learning methods to detect emotions are presented. Third, the result classification models can predict users' moods in real-time during interactions [40].

2) ALGORITHMS AND RESULTS

The section briefly introduces the algorithms were used in different articles and the results for each article. Table 9 identifies corresponding studies with an algorithm in the datasets and the accuracy of the results. Summary of classification algorithms data is provided in Table 8.

According to [32], the SVM-SMOTE oversampling technique was applied to reduce the problem of class imbalance. Seven ML approaches, including K Nearest Neighbor (KNN), Support Vector Machine (SVM), SVM with the sigmoid kernel, SVM with linear kernel, SVM with the polynomial kernel, SVM with radial bias, Logistics Regression, and Neural Net. Table 9 compared for model evaluation. Each classification model was validated using leave-one-out cross-validation during the development process.

The results reveal that the best accuracy was achieved using a combination of SVM-SMOTE oversampling and SVM with a polynomial kernel. The highest level of cross-validation accuracy was 86%. While the study by [38] revealed that the KFCV approach revealed that the EL of the GS algorithm is

(ρ(a) = 0.341486) and the MMHC is (ρ(a) = 2.350423), this suggests that the GS method generates a BN model better suited to the data in this investigation than the MMHC approach. As a result, GS outperforms the MMHC algorithm and is better suited to the dataset used in this study for

TABLE 9. Summary of algorithms.

Algorithms	Description	Accuracy	Source
K Nearest Neighbour (KNN), Support Vector Machine (SVM), SVM with sigmoid kernel, SVM with linear kernel, SVM with polynomial kernel, SVM with radial bias, Logistics Regression, and Neural Net	The classification model building, each model was validated by leave-one-out cross-validation. The results show that the combination of SVM-SMOTE oversampling and SVM with polynomial kernel provided the best accuracy.	SVM-SMOTE + SVM with polynomial kernel 86%	[32]
Bayesian Network (BN)	The proposed ruling user model used a BN probabilistic strategy in this study, in which the contexts and four paper levels are all coupled to create a realistic graphical model.	34%	[38]
Binary decision trees, random forests, AdaBoost, and Multi-Layered Perceptron.	Comparison of Learning Algorithms for Classifying User Emotions (anger, contempt, disgust, fear, joy, sadness and surprise).	Random forests 47%	[40]
Naive Model, Random Forest, MLP, GRU, LSTM	Developed an ensemble of sequence and traditional classifiers, which proved to be the most accurate and lucrative prediction across all models studied.	GRU 43%	[31]

TABLE 10. Summary of classification methods.

Approaches	Description
Support Vector Machine with Polynomial Kernel Function	The optimal line is used by the SVM algorithm to divide n-dimensional space into classes using the hyperplane. The problem is transformed using Polynomial Functions to learn the hyperplane [46].
Support Vector Machine with Radial Basis Kernel Function	SVM models categorize data by employing Radial Basis Kernel Function to optimize a hyperplane that separates the classes [46].
Support Vector Machine with Linear Kernel Function	A separating line formally defines this classifier. The hyperplane is learned by changing the problem into a linear algebra problem [46].
Support Vector Machine with Sigmoid Kernel Function	With the Sigmoid Kernel Function, SVM models process data points by drawing decision boundaries [46].
K-Nearest Neighbors	The label of data points around a target data point is used to define the class label by a plurality vote of its neighbors in K-Nearest Neighbors [36].
Logistic Regression	A technique for predicting a continuous output value from a linear relationship is linear regression. The output of Logistic Regression, on the other hand, will be a value between 0 and 1, a probability [46].
Multilayer Perceptron	A multilayer perceptron (MLP) is a class label classification approach. With one or more hidden layers, it has the same structure as a single layer perceptron. With a binary goal, it can only classify separable cases (1, 0) [47].

BN modelling. [40] claimed that the best average accuracy between the four ML algorithms is a random forest with an accuracy of 47%.

Finally, [31] argue that only two RNN-based designs outperform the naive model across the board. The GRU appears to perform slightly better than the LSTM of these two architectures. Despite this, determining which RNN model better predicts the possible order values of non-purchase sessions are challenging due to minor changes in error measurements.

IV. DISCUSSION

ML is becoming increasingly vital in developing new goods and services to provide a better UX. Understanding ML capability, imagining new goods and services, and effectively interacting with data scientists are all UX designers face today. Our study summarizes the challenges and recommendations for UX designers using ML in their products, services, and websites.

The results of the full-text research for the collected articles are shown in this section. We discovered that these UX designers do not consider themselves ML experts and that learning more about ML will not help them become better ML designers. Instead, participants seemed to be the most successful when they worked with data scientists regularly to help them imagine what they should produce and adopted a data-centric culture and became proactive in their use of data in their design practice.

Below, we discuss how these findings depend on our research questions. We also consider other design research opportunities which can better inform the HCI community about the existing divergence between UX practice and innovation via ML.

A. SUMMARY OF FINDINGS AND DISCUSSION

1) THEMES OF EXPERIENCE

The themes of experiences highlight the attitudes and challenges that designers face while working with ML in the UX design process and why we need to learn more about ML as a design material. In addition, the experience themes different features to enhance UX design practice and draw on studies on designers using ML as a design material. The following Table 11 illustrates the experience themes.

TABLE 11. Themes of experience.

Themes	Description
Absence of competence	Which depicts UX designers expressing missing competencies in order to work more effectively with ML [10].
Lack of motive for competence development	The UX designers expressed a lack of obvious motivation to learn about ML [8][35]
Challenges articulating standard	Designers, poses challenges in terms of articulating design criteria for assessment [10].
Maturity of the customers	UX designers expressed the need to modify their design practices based on the digital maturity of their customers [34].
Lack of ethical concerns support	The designers stated that ethical concerns are sometimes overlooked and not taken seriously and that the current UX design process lacks support for argumentation and discussion [33].

Even poorly organized and fuzzy design projects may be rigorous and disciplined with the correct tools and methodologies. However, this study implies that the UX design practice lacks the competencies to handle scenarios incorporating ML effectively. In contrast to earlier research on ML as a design material in UX design practice (e.g [3], [12], [21], [36]), these studies adds to what we need to know about ML in UX practice from the perspective of a UX designer.

This research [3], [12], [21], [36] helps us to understand the need to learn more about UX designers' motivations to learn more about ML as a design material. In addition, it could help the UX design profession understand how and why understanding more about ML as a design material would be beneficial. Moreover, it could also help UX designers determine whether this should be approached differently than other design materials or deemed a new design material.

According to [3], [12], [21], [36], a lack of ML expertise in UX design practice can have unsettling repercussions. UX designers, for example, must be able to identify design criteria for an experience that prioritizes the user. Hence, to move forward with potentially beneficial ideas to customers and users. One possible result is that the UX design practice should be better prepared with better preparation support measures.

One possible outcome is that the UX design practice should be better prepared with better preparation support measures. The previous studies consistently [17] assert that research must affect UX designers' work. The characterization of the consumer was expressed to be relevant in approaching a design project, as mature vs immature customers imply. The current review advocates for more profound research into customers that employ machine learning in their digital solutions.

Furthermore, the absence of support for ethical considerations suggests that designers working with ML face scenarios where they have difficulty expressing and presenting assessment criteria [33]. This research highlights the need for supporting tools and methodologies to promote ethical arguments in UX design practice, bolstering the designer's confidence and actions. UX designers must be ready for action and arrive with the appropriate toolkit for the project at hand [33].

The results show that most UX designers have lacked a fair understanding of what problems are difficult for ML to solve, which is especially important for customizable applications that use transfer learning to contextualize ML models. However, the results show that most UX designers have a fair understanding of what problems are difficult for ML to solve. Since this only refers to the specific set of ML capabilities used when working with datasets, it does put into perspective claims in the previous sections in this review. UX designers frequently have misconceptions about ML functionality [8] or have difficulty understanding the restriction of what ML can learn [39].

2) TOOLS

As a result of our research approach, we argue in this review that ML tools should not be "pushed at creative minds" simply because they are technically possible to build. Instead, they should be informed and produced through a thorough examination of existing design processes. As a result, introducing new tools may alter how designers think about and approach their work.

Tools focus on the changeable nature of ML-enabled UX design and allow designers to contribute to the material's growth. Unfortunately, ML has remained underutilized to assist designers, and it has yet to be fully integrated into design patterns, education, and prototype tools [12]. Within the concrete design process used by an industrial partner, [39] studied integrating ML into early GUI design stages. [39] reported that an in-depth development process for an ML-based tool concept for UI/UX designers.

Microsoft Custom Vision was used to develop and test a model for detecting GUI elements in photographs of paper sketches as a compromise between quickly developing an ML-based app and making accurate predictions. Microsoft Custom Vision already comes with a high-quality foundation model trained on a large amount of generic image data. The main limitation in the study of [39] was prototype's ML model was trained on a small set of sketches. At the same time, real-world applications necessitate more in-depth instruction in a broader range of concepts and more complex user interface designs.

Therefore, the current implementation of [39] is limited to a prototype level. Still, it is incorporated into a well-known tool (Sketch), allowing us to explore practitioners' perspectives within the framework of a real-world design process used by an industrial partner.

According to [48], attempts to integrate the ML development process into traditional conceptual design processes, in which designers consider ML, users, and the situation as a whole. The Canvas tools it's only good for the conceptual stage and can't be utilized for prototyping. This tool is also limited to UX designers; it can unite professionals from all fields.

Therefore, tools are still in the early stages. Finally, it cannot cover all conceivable questions, and the question list may limit creative design activities. In addition, we found that all developed tools are still in the conceptual stage and cannot undoubtedly be used in prototyping. Also, we claimed that the tools were not designed with the participants of UX designers. For that reason, tools are still in the early stages.

Furthermore, we claim that the tools were not created in collaboration with UX designers. However, because current conceptual design tools aren't specialized to the ML context, there isn't yet a design process or device that can help designers think of new and practical ways to use ML. The lack of research encourages designers to engage in the expanding circle of ML by developing design methods that consider ML, users, and the situation. As a result, a strategy that bridges the gap between conceptual frameworks and detailed instructions for designing tools to improve the UX design process is necessary.

3) ALGORITHMS AND DATASETS

Data classification is essential since it instructs the system on classifying users depending on their behaviors. ML algorithms can categorize user behavior, which can aid UX designers in indicating the use of declared terms in prior user sessions. However, knowing how ML systems work is not the same as knowing where and how to include them into the UX designs process because "many of these algorithms have poor linkages to varied user experiences after repeated use".

UX designers must recognize unexpected user requests that are theoretically satisfactory using ML. Due to the increased usage of ML in the design process, the data scientists are the following UX designers. ML can be considered a tool to improve user experience because of its capabilities and issues. However, ML is a difficult medium to build for or with due to its many complexities. The performance of several ML capabilities was scored in a wide range of ways by UX designers; though, above-par mean ratings for all abilities show that most designers are positive about ML capabilities.

Implying that these issues may implement minimal to well-defined generic ML problems UX designers may have heard of or read about, such as object recognition or face interpretation. This type of debate has yet to occur in the design of ML. What are the unique qualities of ML in terms of increasing UX? What are the differences in its experience features among algorithms or datasets? Answers to these issues would allow for a more thoughtful and disciplined.

How to make ML available to UX designers and enable design-led ML innovation? It would also help UX experts determine whether and how ML instruction for UX designers should differ from non-ML professionals in general. According to Table 6, the data collection methods are Video Capture, Survey Log Data, and User Sessions. Video capture is a method that uses 72 videos captured for facial expressions was chunks to 1-minute video. Then system analyzed the captured videos as 72 facial expressions to numeric data to build the dataset [32]. After that classification model building, each model was validated by leave-one-out cross-validation. The results show that the combination of SVM-SMOTE oversampling and SVM with polynomial kernel provided the best accuracy. However, one limitation of this study is the small number of samples. Therefore, larger sample sizes are required for further validation of the approaches.

At the same time, the second method to build a dataset is a survey [38]. The data collection survey was conducted for 1.5 years and resulted in 1121 records. After that, the 675 participants entered the paper IDs, and 446 participants uploaded the PDF files of the relevant papers, according to the data collected. However, ten records of users' data were found to be invalid, and 58 PDF files were found to be meaningless and irrelevant. As a result, 68 invalid records were removed from the dataset, leaving 1053 records in total. Nevertheless, the sample size of a dataset was small, leading to less accurate results [38].

Log data is another method used to prepare a dataset by creating a plugin that users can install in their browser [40]. This plugin takes a photo of the user's face from the webcam every 2 seconds and mouse and keyboard logs. The critical shortcoming is that it is impossible to maintain track of absolute test reliability: users may choose to ''rush'' the test or be influenced by the testing environment (a problem that also affects ''traditional'' approaches), causing the final findings to be distorted [40].

User session is the last method in this review [31]. The data was acquired between May 20th and July 20th, 2018, covering user sessions from an online shop's website. The dataset did not include information on redemption possibilities. In addition, Koehn *et al.* 2020 acknowledge that research has a more general drawback, which derives from our decision to use conversion categorization as a vehicle for e-coupon targeting [31].

Finally, it is worth mentioning that no studies used a benchmark dataset where the results will be more accurate than other studies. Analyzing clickstreams of user sessions, extracting useful information, and making predictions about their interaction behavior are critical solutions to improve UX depending on each user behavior. Incororating benchmark datasets to enhance UX design using ML techniques is still missing. All the studies are confirmed that the fields of ML and UX design have still lacked in the following:

- Lack of awareness among UX designers of the importance of using ML algorithms in improving UX design and challenges facing UX designers when incorporating ML techniques [8], [12], [36], [49].
- Lack of research on ML algorithms and UX, especially in envisioning how ML might improve UX [10].
- In addition, the studies emphasize the importance of developing and testing a model to collaborate both ML and UX [7], [49], [30].

4) ALGORITHMS AND TECHNIQUES

The term ''technique'' covers a wide range of approaches that can be utilized to achieve progress on various issues. Because it's so broad, it's usually not specific enough to the specifics of any given problem to offer a single answer. Instead, the solution to an issue may necessitate a combination of different approaches. Koehn *et al.* (2020) reveal that all possible combinations of hyperparameters are evaluated in random order. These 200 distinct classifiers are then applied to each method. Next, the area under the receiver operating characteristic curve (AUC) on the current holdout fold is used to evaluate each fit. Finally, the combination of hyper-parameters of the model with the highest average AUC overall ten folds is selected for subsequent comparisons on the test set [31].

It is essential to mention that cross-validation tuning demand value estimation methods avoids details leakage from the test set. The benchmark is inspired by Baumann *et al.* (2019), who utilize this approach to assess order values [50]. The features considered in the study of [50] observe a matching logic of value estimation methods. Following [40], compared several learning methods, including those that had previously been employed, such as binary decision trees, random forests, AdaBoost, and Multi-Layer Perceptron.

A forward feature selection technique was used to find the optimal collection of features for each type of model. Because emotions are essential aspects of UX, some authors are experimenting with ML algorithms ([51], [52], [53]) to recognize users' emotions by monitoring their interactions with the system (e.g., mouse movements).

V. LIMITATIONS

Our investigation demonstrated the associations between UX design using machine learning. Previous research suggests that design practice lacks understanding of how to work with ML as a design material effectively and how it can add value to their practice. Some research is still in its early stages, with inaccurate results. Other studies are still in the conceptual stage and cannot be used for prototyping. Also, the implementation in a working environment has been investigated yet.

However, a more accurate prediction model would be preferable, which might be achieved by increasing the number of samples utilized in the training phase or the number of participants in the data-collection phase. In addition, the sample size is limited to selective groups, genders, and distributions. Additional validation of the methods requires investigations with larger instance extents. Tools in section 3.2 were trained on a bit of a set of drawings tailored.

VI. FUTURE DIRECTIONS

The results of this peer review revealed a significant amount of evidence and recurrent concerns about UX design issues and recommended strategies using ML, the impact of these perceived issues, and the effectiveness of strategies to incorporate ML into UX design. This knowledge will be an invaluable insight into fully understanding the scope of machine learning's capabilities and techniques to express UX designers' concerns about their effectiveness in their actual efforts to access, execute, or communicate the UX design process.

Further research is needed to explore these areas to promote and improve our understanding of ML capabilities and improve design issues related to the UX design process. In addition, developing web-based tools using users' behaviors and sessions data integrated with ML algorithms to enhance UX design is a promising research area with more challenges and directions.

VII. CONCLUSION

This study presented a systematic review indicating the UX design using ML from UX designers and experts' perspectives. The majority of the UX designers who took part in this research had no expertise with ML as a design tool.

This suggests some of these issues may arise because of the novelty of using ML as a design material. On the other hand, we discovered valuable academic work already with ML for UX.

We believe that creating such a study will positively impact UX design, benefiting both users and designers. The implications for ML development, testing, and feedback collection could be huge: not only would more models improve the quality and breadth of feedback. Furthermore, the development of said rougher models would save significant time in the early stages of app development (where feedback is most important), pushing the polishing of the user interface to the later stages. This could have influenced the outcome, implying the need for a follow-up investigation in the future.

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