# Machine Learning and AI Application Behaviour Prediction for User Experience Modelling and Optimization

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**Abstract** – The purpose of this research is to offer a technique for assessing user experience in mobile applications utilizing AIAM technology. Due to ineffective and time-consuming nature of conventional data gathering techniques (such as user interviews and user inference), AIAM concentrates on using Artificial Intelligence (AI) to assess and enhance user experience. Logs from a mobile application may be used to gather information about user activity. Only a few parameters of data are utilized in the process of surfing and running mobile applications to ensure the privacy of users. The method's objective is to create the deep neural network prototype as close as feasible to a user's experience when using a mobile app. For particular objectives, we create and employ application interfaces to train computational models. The click data from all users participating in a certain task is shown on these projected pages. User activity may therefore be mapped in connected and hidden layers of the system. Finally, the social communications application is used to test the efficacy of the suggested method by implementing the improved design.

**Keywords –** Artificial Intelligence-Aided Model (AIAM), Artificial Intelligence (AI), Human-Computer Interaction (HCI), Deep Neural Network Models (DNN).

## I. INTRODUCTION

Humans are increasingly striving to communicate with machines in a more conventional manner because of the fast growth of digital technology. In the modern age, it is no longer natural to communicate with computers using input devices like the mouse, keyboard, or remote control since they lack flexibility. Most online commercial items and most people's PCs can be communicated with by using body language and voice instructions. The most essential use of machine vision for unsupervised systems is the communication between individuals and computers. For optimal Human-Computer Interaction (HCI) [1], it is vital to collect exact data, such as the form, behavior, and movements of the user. These human targets as demonstrated in **Fig. 1** may be reliably identified and recognized by an effective examination human sensor technology in Human-Human Interaction (HHI)

There are several hurdles that must be overcome before computers and humans can communicate with each other. During human-to-human interactions, we can quickly identify each other's age, gender, facial expressions, and gestures, among other things. Contextual data such as the setting and speech context is conveyed through visual cues/features that influence conversational content. Gestures like this one might be utilized as a signaling of comprehension, or the gaze orientation could be used to distinguish between this item and that one in speech. As a consequence, nonverbal means of communication like voice and hand gestures work in tandem with and in addition to visual medium of communication.

Conventional sensors, on the other hand, do not provide a sufficient field of view for monitoring multiple objectives, such as human mobility and body characteristics. It is necessary to have enough room to map order gestures and distinct human targets throughout the human movement recognition procedure. Human objectives and surrounding items must be recognized, and the computer strives to meet those needs for the human engagement environment. i.e., the user's action should be linked with the gestures in the virtual field; i.e., it is more suitable to anticipate the gestures for HCI. By merging visual information with different input modes, a rich consumer experience and more efficient interaction may be achieved (such as keyboard and mouse). Vision-based interaction might be useful in a range of computer settings outside the traditional desktop, such as mobile, immersive, and omnipresent.

When it comes to HCI, sensors like electromyographic (EMG) and sensor fusion have become more commonplace (see **Fig. 2**). It is possible to evaluate and simulate muscular functions by using captured, filtered, magnified, transmitted and fed bioelectric data from electrodes on the skin's surface that gather bioelectric signals from superficial muscles and nerve trunks. Human leg and hand EMG signals are susceptible to noise interference during item use. Gathering data, extracting characteristics, and categorizing different hand motions for HCI is the most challenging part of interpreting hand motion. Identification of human targets/emotions is achievable from an object's physical qualities such weight, size, and form.

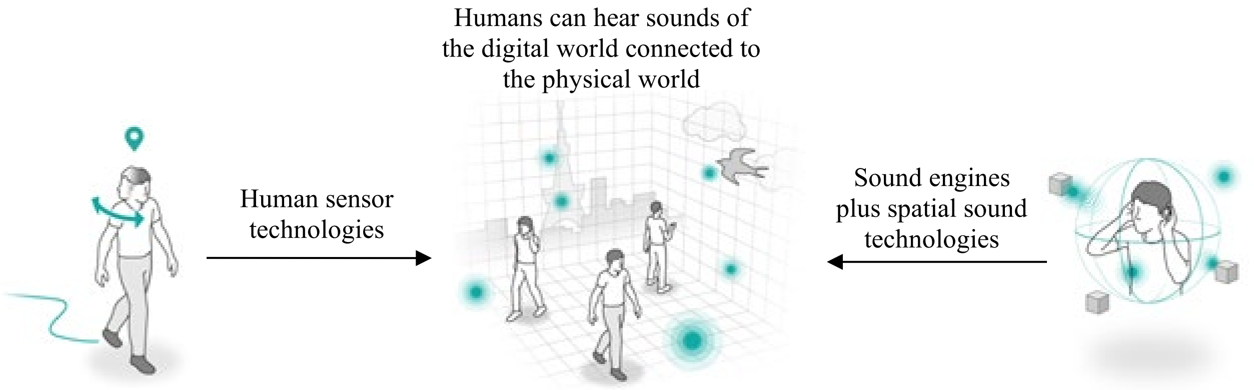


**Fig 1**. Human-Human interaction

More and more people are accessing services and information through their mobile devices as the mobile Internet grows. Smartphones and tablet PCs with high-density HCIs are becoming more popular. Mobile devices are being used to introduce a wide range of programs, including social transport letters and health care and leisure apps.

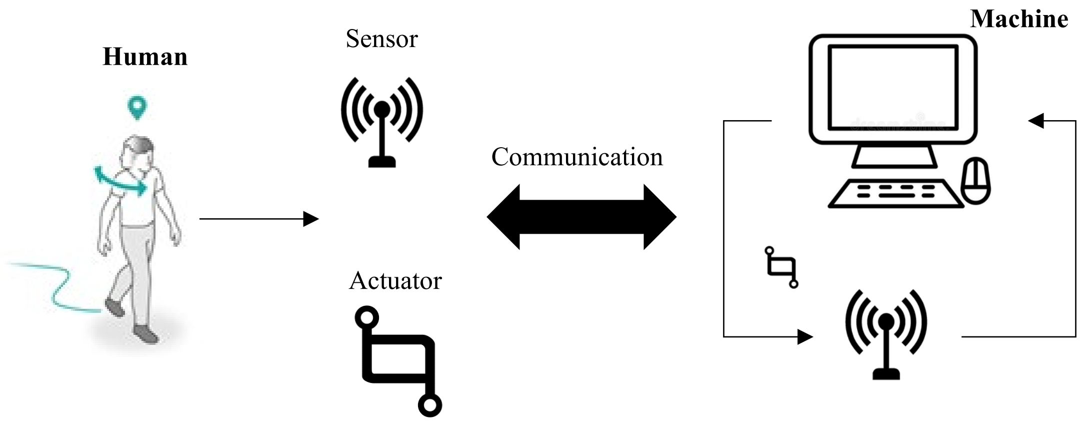


**Fig 2**. Human-Computer Interaction

Apps for mobile devices may currently number in the tens of thousands. While this may be true, mobile apps are becoming more similar in design. Many businesses struggle with the issue of creating distinct competitors. Enterprises are also attempting to make a breakthrough in this area. Customer loyalty has become an increasingly important factor in the success of many businesses. As a result, enhancing the customer experience of goods is the most lucrative economic potential for organizations. This examines the Artificial Intelligence-Aided Model for assessing user experience in mobile applications. The remaining sections of the paper are organized as follows: Section II presents a background analysis of the research. Section III focusses on evaluating the previous literature works. Section IV critically discusses the measurement of user experience. Section V presents the methodology employed in this research. Section VI presents the results and discussions for this research. Lastly, Section VII draws finals remarks about the research and proposes future research directions.

## II. BACKGROUND ANALYSIS

In the realm of Human-Computer Interaction (HCI), the term "user experience" has gained a lot of traction and popularity. According to Porcu, Floris, and Atzori [2], Norman is often credited for coining the term "user experience" in the early 1990s. Increasingly, subjects like psychological, user testing, HCI have been evaluated in the essential domains of user experiences as its connotations and structure have expanded. Focused on the non-utility of HCI, user experience concentrates on the manner in which the user's emotional response to a technology affects their everyday lives. as a consequence, the term user experience has come to be considered as acceptable, although what exactly it signifies is still up for debate.

The value of user experience is becoming more widely accepted, yet no one has agreed on what it means exactly. User experience experts' notions of accessibility and user experience were explored by Emberton and Simons [3]. Results from various nations and social–cultural groupings were compared. Different user experience specialists have different definitions of what constitutes a good user experience, and there are also disparities based on things like social and cultural context. In Finland and France, experts in user experience place an emphasis on the description of experience characteristics, but in Turkey and Malaysia, they place an emphasis on the description of usefulness, ease of use and attractiveness. The subjective emotions of the user, however, will leave behind a trail of evidence. Concrete evidence or experiments may be used to characterize and quantify them.

According to Miller and Reed [4], "user experience" is defined as the individual's responses and perceptions, which amount from the usage or projected usage of a service, product or system. User experience typically concentrates on the person's experiences with respect the usage of a particular product. As per [5], the ideology of "usability" is presently widely accepted in the field of user experience. The study in [6] examined six regularly used questionnaires to assess chat systems to see whether they might be used to measure various aspects of the user experience. On the other side, if the product has a strong usability, consumers will find it easy, quick, and pleasant to use, reducing the risk of user error. By making people feel good emotionally, it will accomplish the goal of enhancing the user experience. User experience is defined in ISO 9241-210, and our goal is to enhance the way users interact with mobile apps by adhering to that standard's guidelines for user experience design.

Using a three-dimensional paradigm, [7] outlined 20 typical methodologies for user experience research in order to better know when to apply them. Methods for studying user experience may be split into behavioural and quantitative dimensions. Some huge and extensive media applications (e.g., WeChat, Weibo, and QQ) have been excluded from the China's market, where social networking has become more and more mobile. There are a variety of apps that cater to a wide range of social communication demands. Using a vertical social app offers the advantage of a distinct service area and great relevance. Vertical social APPs are just as important as one or two major social APPs when it comes to serving a single purpose. Identifying the specific vertical users is, thus, a vital consideration.

Users in China, for instance, are more likely to utilize a single app or a small number of apps to do a single activity. It's expected that users will be able to keep tabs on the overall progress and allocation of tasks. When many activities are combined into a single process, cognitive resources are freed up for the user to employ as he or she works on other tasks. Users will fight for psychological resources if the "large and comprehensive" application's subtasks are less important and the task procedure is not coherent, resulting in users roaming and switching between various activities, which is unsatisfactory for overall efficiency. Developing and maintaining user loyalty in a dominant social APP market is very difficult for a vertically integrated social app. It is a social network for the drainage and sewerage business. There is a problem with the app's user engagement and user retention. The application was then optimized using the recommended technique. Artificial Intelligence Assisted Model Methodology (AIAM) is designed to imitate the user's experience when employing various functionalities in Deep Neural Network Models (DNN). Section III provides an analysis of the previous research on DNN, product development, and user-experience models.

## III. LITERATURE REVIEW

### *Deep Neural Network (DNN) Model*

In 2006, Angelov and Soares [8] published their groundbreaking work on Deep Neural Networks (DNN) in the *Neural Networks scientific Journal*. Essentially, the DNN framework is first split into a series of two designs before we learn the entire design and then layer by layer, we prepare the two-layer neural system architecture and eventually get the relative weights of multi - layer neural networks by creating the qualified two-layer neural networks. This layer may be used to extract the elements from the input since it is abstracted in the neural network. As a result, neural networks with several hidden nodes are better at digesting and generalizing networks, and reach a higher rate of convergence.

Each node in the same hidden units may utilize the same non - linear function to transfer inputs from the level below to the existing node in a feed-forward deep neural network with many hidden layers. The various hidden units and three hidden nodes of the DNN structure allow it to adapt to the nonlinear connection between outputs and inputs with great ease. If you're looking for regression or classification, a DNN model is usually the best option. Although the model is classified as a classification model in this research, we do not standardize the incentive value of the DON's final layer into an integer in order to get continuous suspiciousness values. By constructing a cost function based on the discrepancy between the desired and actual outputs, we may use backpropagation (BP) to teach the DNN. An important part of creating a DNN model is choosing how many layers, nodes, and transfer functions there should be, just to name a few considerations.

### *Product Development*

For the optimal product design in the beginning of the product development lifecycle, numerous observation techniques have been developed to collect and assess user experience. Measurement, focus, and pragmatism are the three kinds of user experience methodologies that Goldstone [9] successfully categorize. Physical responses and subjective perceptions of the body may be directly quantified using measurement techniques that concentrate on all elements of the user experience. Through a variety of formal approaches, such as textual and visual information, as well as creative activities in the design stage, it is possible to get a deep insight of the user's wants, desires, aspirations, and intentions. Rather than analyzing the existing customer experience of the system, these techniques try to plan the prospective user experience and inspire designers. User experience is seen holistically through pragmatic methodologies, which concentrate on the interaction between users, technology, and the environment. Interactions between humans and machines are referred to as "interactive interfaces" by Bertino [10]. Semantic web and Artificial Intelligence (AI) are expected to produce an enormous quantity of online information in the near future. We think that customer experience can be learnt by a computer based on existing AI-based measurement and comprehension approaches. In this part, we'll provide a quick overview of the three connected works.

*User-experience Models*

*User Experience Based on Flow*

To put it another way, "a delightful encounter in which a respondent feels a significant amount of behavioral control, contentment and enjoyment" is what the term "flow" refers to while participating inside a virtual world. In a virtual world, the authors suggest a model whose components are organized around the notion of "flow". Interactivity, participation, vividness, skillfulness, difficulty, intense focus, flow, telepresence, positive influence, and loyalty are some of the 10 components of their approach. Their theory holds that users are said to achieve a "flow state" when actively engaging with and feeling a connection to the virtual world, when their abilities and the level of difficulty of the task at hand are in harmony, and when they have a sense of being "telepresent" inside it.

Furthermore, this model shows that vividness enhances the user's engagement and enhances the experience of telepresence through stimulating the user's sensory impressions. Having a high degree of engagement (expert/novice differentiation, significance) enhances the possibility of creating telepresence, raises the user's challenge, and produces the user better abilities. Increased user focus (i.e., attention) on the current activities, enhanced perceived challenges for even the competent users, and enhanced user impression regarding the control abilities were also discovered by the authors. For example, they found that the user who is more focused on stimulus in the virtualized environment sees greater levels of presence in the virtual world. This results in a favorable effect on users' attitudes and their desire to utilize the virtual environment again.

*User Experience Based on Continuance and Acceptance*

Virtual environment usage is described as the user's activities and judgments on how they will utilize the environment in the future. The user's aim to utilize the system indefinitely is referred to as their "continuance intention." This approach is based on the acceptability and continuation theory in the setting of the virtual learning environment. Intention, past experience, perceived ease-of-use, perceived utility, pleasure, validation, flow, presence, and immersion are all part of this concept. Flow, presence, and immersion, according to the authors, are all interconnected and affect one another. According to their findings, consumers were able to validate their expectations about the technology via immersion, flow, and presence. In their study, they found that user happiness is affected by consumers' perceptions of utility, ease-of-use, and confirmation of the quality of technological services. Authors have discovered that users' desire to stick with their current technology is greatly affected by their past level of happiness with it and their prior knowledge of how to utilize it.

*User Experience Inclined to Virtual Ecological Features*

Using a model developed in the perspective of virtual environments for enjoyment, Schellekens, Ramsey and Raemaekers [11] identified the characteristics (i.e., visual motion, stereopsis and field of view regularity and degree of interactive elements) that lead to an optimal user experience (i.e., visual initiatives predictability to visual motion). The three components of the authors' definition of the user experience are: presence, pleasure, and simulation sickness. No particular association exists between simulator sickness and either presence or pleasure, but they believe that a drop in presence or an increase in the severity of the illness is caused by a fall in the level of pleasure.

*User Experience and Interaction*

The interaction between a user and a technological system is captured in a model presented by Hrimech, Alem and Merienne [12]. Users' emotional reactions and the repercussions of their user experience make up the other seven components of this model, which are characterized as aspects of the system and their own traits as well as factors of the setting in which they engage with technology. Defining the components that affect the user experience integrates the system features, user traits, and context parameters. According to the author's findings, system properties (e.g., the number of fulfilled tasks and the time taken on every task have a direct impact on the user expertise (i.e., instrumental and non-instrumental customer satisfaction as well as sentimental user responses) and the effects of experiences (i.e., general judgement and alternative decisions). According to their strategy, the traits of users effect the subjective sentiment and the environmental factors affect total judgments. User responses are also impacted by both instrumental and non-instrumental quality assessments, according to the model presented in this paper. As a result, this shows that the implications of the user experience are dependent on both instrumental and non-instrumental qualitative evaluations, as well as emotional user responses, as well.

## IV. MEASUREMENT OF USER EXPERIENCE

Since the 1930s, psychology science has gathered behavioral traces. Participants in this study were instructed to stop at various points throughout the experiment, and the results were documented in real time. Hedonic quality may be measured using the AttrakDiff questionnaire, which is one of the commonly employed standard query in HCI. The Hedonic quality is measured, but it also takes into account the practicality and attraction of a product. Using the Kim and Yoo [13]' user experience paradigm, AttrakDiff has a solid theoretical foundation. In the model, hedonism and practicality are seen as the two major attributes of a product. Hedonic quality and pragmatic quality are terms used to describe the capacity of product endorsement to accomplish a goal.

Three categories: practicality, hedonics and aesthetics make up the 28-item list. Although it's worth mentioning, the AttrakDiff theoretical model does not seek to quantify emotions like pleasure, contentment, joy or rage since they are believed to be the outcome of the cognitive evaluation process. The Daily Reconstruction Technique (DRT) established by authors in [14] was used to study the rich quality user experience and to elaborate on the idea of user experience in story form. Six persons were observed over the course of five weeks as they made their way through the Apple iPhone purchasing process. Long-term usage was more motivated by various features than by giving a great first experience, according to their findings.

Traditional techniques of collecting data from users and extracting feature models from those users, on the other hand, are ineffective. As the volume of user data grows, so does the expense of research and development. Big data and machine learning, on the other hand, have grown quickly in the last several years. Use these tools to aid in the creation of a design, and you may save time and money. According to Jun and Peng [15], numerous sorts of behavior data may be used to improve a design. A product or service's success or failure may be analyzed using log files, they say. A behavior log is a record of a user's action that is seen via the lens of a sensor. It includes anything from simple keystrokes to full-fledged audio and video capture. Lab studies, field research, and log studies are all examples of user behavior data gathering methodologies.

Another benefit of using logs is that they can be captured on a big scale with relative ease. It's common for laboratory and field researches to have just a few dozen participants; journal studies might incorporate data from millions of individuals. Even the tiniest changes across populations may be seen thanks to a big sample size. The unique but crucial piece of behavior data provided by large-scale logs is difficult to collect in smaller research. Genetic algorithms are used to categorize various sorts of user activity data in log files. In information retrieval systems, genetic algorithms are often employed to improve the process of retrieving information. Evolutionary algorithms were used in text data acquisition by Ling and Lam [16]. In the years that followed, the author developed a number of text clustering approaches that aided in the advancement of text clustering techniques. According on user behavior records, the next section introduces many well-known click models.

*Click Patterns*

In recent years, experts have been more interested in the use of information in the software development process to better comprehend decision making. The use of click models to describe or foretell the activities of users has become widespread. There is a large amount of click model research that is based on the most fundamental study. Search engines are considered to be accessed from the top to the bottom of the search results page. Search results are arranged in a logical sequence, according to this premise. Depending on the region, almost all of the click patterns are used. As a consequence, the click model relies heavily on user interaction data (mostly click data) to make inferences about user behavior and correlations between user actions and results. As a consequence, these models consider that all the search results on the page are the same in terms of content (all these are uniform in form, only varied in terms of content, relying to the model, only distinct in the relevancy of their results). In the absence of applicability, these findings have no influence on the user's actions.

Logs of clicks may be an important source of data. Because of its location in search results, it might be difficult to create a click model that accurately predicts how many people will click. A Cascade Model (CM) was presented by Timothy and Meschke [17] to deal with such bias. On the basis of this, they assume that users would scroll down the search engine results page until they find a link to the content they need and then click it. If "the chosen user will never return, and the rejected user would always stay," then Canonical CM limited its search operations to one click. The authors' suggested Probabilistic Graphical Model (PGM) is distinct from CM models. Each search result action is broken down into a sequence of apparent and secret occurrences in the PGM structure. Mathematically, it gives a trustworthy approach to deduce a collection of occurrences provided some other data.

Most probability frameworks distinguish between the occurrences of a user looking at a website and a user being pulled to a content. Generally speaking, these events are seen to be unrelated to one another. To make matters worse, most of these models presuppose that the users would only click on documents they want to examine or find visually appealing. User Browsing Model (UBM) addresses this issue. Users may be split into three groups based on the usage of online search, which is used to analyze the individual behavior of users, as well as to forecast what users will do next. UBM concentrates on the latter, which exclusively relies on online search logs for its data. UBM can predict the likelihood of a document being inspected based on the order in which documents are ranked and the range from the most recently clicked documents. A Bayesian inference approach is used to estimate the posterior distribution of the important parameters rather than a probabilistic estimator or an expectation-maximization procedure. Sagar, Srivastava and Arora [18], drawing on UBM's assumptions about user behavior, suggested a Bayesian Browsing Model (BBM). In order to evaluate the model's usefulness and efficiency, series of experiments were conducted. The experimental findings reveal that BBM is a single-channel and parallelizable approach capable of exact reasoning.

The test probability models used by various click models vary. Various parameters are used to estimate the attractiveness of a person. Manual configuration is required, however, for the event dependency structure. The handcrafted dependency sets for various click models are different. Simple information like reaction time and click position may reveal people's desired information, according to Souissi and A. Ghorbel [19]. These data may be gathered at almost no cost. Individualistic respondents were shown to be more likely to click on their own rewards than on the rewards of others. In addition, the data on reaction time and click location work together to provide light on individuals' preferences. Web designers often employ regular click-location analyses to improve their work.

By testing with various user behavior hypotheses and developing more advanced models, previous click modeling work has made tremendous efforts to reduce the significant bias and improve the correctness of relevance estimations. The goal of click models is to get correct relevance input from user clicks, which are often noisy and biased. Click model correlation estimation's dependability and correctness must be evaluated as well. There are several pieces of information that may go into creating a click model, including data on the user, her present duties, the way search results are presented, the substance of those outcomes, and other search-related features. According to Lu [20], a new customized click framework was presented to represent the click preferences of individual users. From a collaborative filtering approach, this paradigm extends matrix/tensor deconstruction by linking users, requests and texts together.

It is possible to combine this model into the click model, which is a generic framework for customizing Search click data is limited, but by using possible eigenvectors, the models can pierce query and document, even for uncommon or novel query document pairings. Many locations have little, if any, data from even the most basic forms of monitoring. The query generation algorithm is developed using broad domain information, but it is then applied to papers from a specific domain. A large number of noisy, domain-specific query document correlation pairs may now be created. You may then use zero-shot optimization to create a retrieval model based on your search query. Users will be unable to perform a job if they just have access to the click position. Optimization techniques to the sequential information sampling issue led to a constant link between reaction time and preference intensity. Hashimoto and Yotsumoto [21] found that the reaction time corresponds with the preferences of the people studied. People's preferences were inferred from their reaction timings and click placements. In our suggested paradigm, reaction time is also taken into consideration.

As of late, Sisodia and Sisodia [22] have developed a new online review click location and user publishing behavior model based on a data-driven agent model. How many major reviews and answer reviews are posted based on a user's click position is explained in the model? The quantity of items per site has a moderating influence on the association between click position and posting behavior, which is also examined in this study. There are five different ways to click in this game. A participant's publishing behavior is determined by his or her capacity to comprehend the information and his or her understanding of the subject matter. When designing a mobile application, clicking orientation may also be utilized to simulate the user's experience.

In recent years, researchers have turned their attention to analyzing search engine results pages using a click model. Search pages now have a huge number of results with rich text content. There are a number of smaller search engines, or "vertical search engines," that specialize on a particular kind of search. So, because of this heterogeneity in search results from longitudinal search engines (e.g., the picture results returned by an image search engine), it is possible that the current user's habits of browsing and their preference might change significantly due to these modification in the results of serarch. The vertical results, in many formats, have enormous effect on the behaviours of users, and this includes the lateral results (local impact) as well as the overall look and feel of the search results page, according to Jiang and Okamoto [23], who examined the massive search log data of a Chinese promotional search engine (global impact). Resultantly, distinct vertical outcomes must be taken into account. Users' changing browsing habits were thoroughly investigated, and the results led to the formulation of the following bias presumptions: (1) interaction bias theory; (2) imperialistic tendencies bias theory; (3) first-bias effect theories; and (4) surfing order bias effect theories, all of which were summarized in the final report.

*Behavior Data*

Assuming that user click behavior is influenced by bias, the click theory may infer behavioral effects and correlations between individual operations. It is possible to generate a correlation estimate with a slight departure from this model's click pattern after retraining it. Ranking characteristics such as click-based relevance estimates may be trained into a learning-to-ranking model using this example. In order to train and assess “data-hungry” neural ranking frameworks, these features can be utilized as weaker monitoring indicators.

One of the most challenging aspects of data retrieval is dealing with geographical discrepancy. Using traditional approaches has two major drawbacks: To begin, when a user clicks on a page, the contents of the chosen document are normally disregarded. Second, they just take into account the geographic variation and do not take into account the other issues created by the surfing habits of consumers. A click model's correlation estimate should be as exact as feasible in order to optimize the execution of follow-up duties. There are two main criteria that determine how accurate an estimate may be: accuracy and authenticity. While the aspect of precision is regarded as the evaluation of error variance, the aspect of validity alludes to the measurement of the available errors in programming (i.e., estimation variance). Click model correlations should be examined for their trustworthiness, according to Devi and Sirsi [24]. Correlation variables may be estimated using the variable decibel approach rather than the point assessment method. Point pair correlation estimate is characterized by a reliability metric derived from the posterior probability.

Recent years have seen the effective application of deep learning methods (shown in **Fig. 3**) to problems such as image comprehension and data mining. For example, Deep Neural Networks (DNN) may harvest high-level abstract data, such as human action identification, by employing a deep learning approach As a result of the pre-training procedure and an increment in the overall layers' number within the hidden node to 7, neural network gained "depth" in the truest sense and provided a springboard for deeper learning to take off. Relu and Maxout transfer function substitute gaussian in the basic DNN structure to prevent gradients from disappearing. Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN) and other forms of neural network models have been suggested for the study of user behaviour patterns.

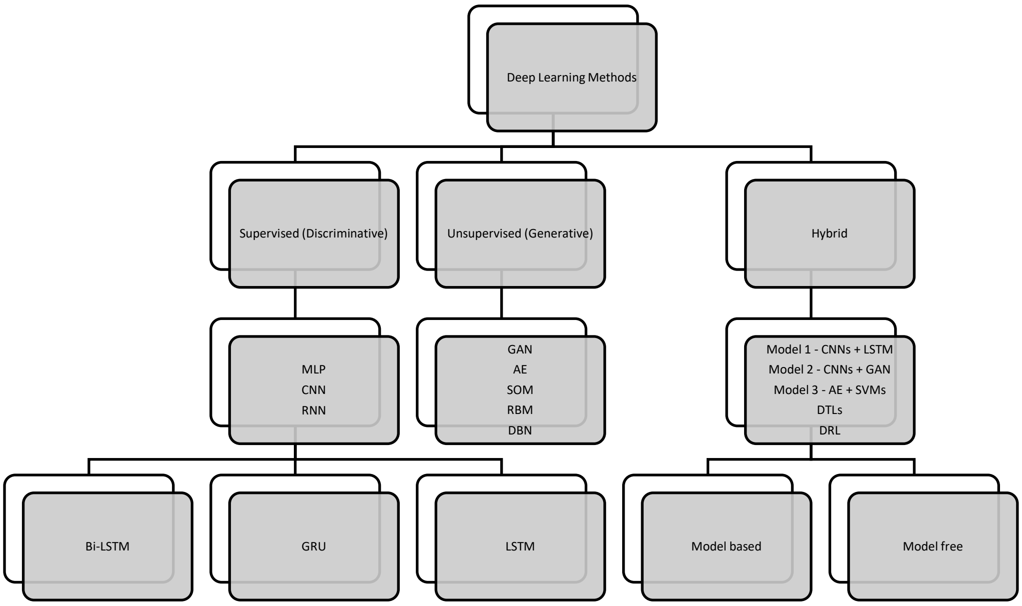


**Fig 3.** Different deep learning methods

Müller, Keil, Kissler and Gruber [25] suggested a neuronal click paradigm for online search based on the concept of distributed representations. Users' data demands and accessible information are represented in a vector state. vector states are used to represent user activity. A query session is described as a series of vector states that represent the user's actions. The initial state of the vector is set by the query, and it is then repeatedly modified in response to the data that is exchanged with the engine. In information retrieval, dealing with implicit yet biased customer feedback data is one of the most challenging aspects of location variation. Debiasing, on the other hand, uses reverse tendency weighting to gather user input. There are two issues with this approach, notwithstanding its practicality. When asserting a user's click, contextual data, e.g., checked pages, is typically overlooked. Second, just the variance in location is taken into account, ignoring other issues caused by the user's surfing habits. Contextual information has recently been modelled by Sagl, Resch and Blaschke [26] using RNNs to predict the conditional probability that users will provide their input at each location. Survival study is used with a probabilistic chain in order to recover the right joint distribution for user behavior.

## V. METHODOLOGY

Mobile application concepts have also seen significant adjustments and developments as a result of the fast advancement of AI technology. Several AIAM approaches were included in the design of the algorithm. The five phases of the envisioned AIAM framework are as follows:

### *Data Collection*

The activity of retrieving and assessing data on particular variables in the existing program is known as data collection. What kinds of information on the users of mobile apps should be collected? Most people may be hesitant to provide too much personal information. A less amount of personal data from users is preferable. With respect to the rule of spatial consistency based on the mental framework , only two forms of user behaviour data can be gathered in our suggested data collecting function. A mental model for HCI must have a spatial component.

Using menus, searching for data in hierarchical file management, and navigating the User Interface (UI) correctly all rely on spatial awareness. A mobile app's mental model space must be consistent to ensure its success. The material representations (symbol, text, visuals, and design mode, among other things) and feedback on various interfaces provide logical constancy in brain space during the course of a work. Consistency in size, layout, texture, and other factors are all part of this. The logic and effectiveness of mental models may be gauged by looking at how spatially consistent they are. For example, in this approach, just a few pieces of information are required (such as the page, the button, the location of the press and hold, and so on). As each click is traced, we may learn more about the user's habits by plotting them on the website. Consequently, just the page id and coordinates, as well as the page's retention duration, are gathered.

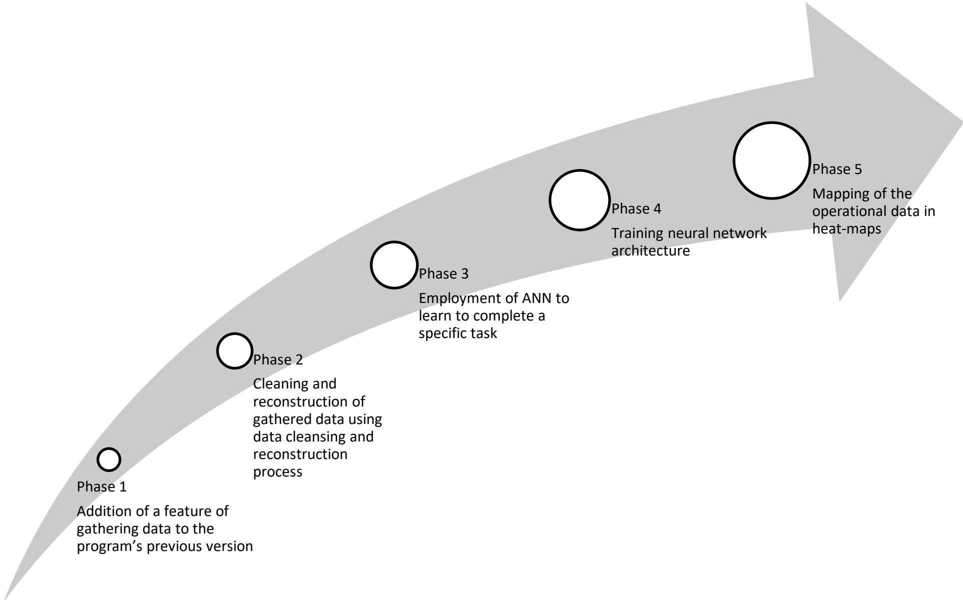


**Fig 4.** 5 Phases in the AIAM framework

The labelled user's data is used in the fifth step of the optimization plan. It's possible to detect flaws in the design of functions and interfaces by looking at failure logs. In the last step, a trained neural network structure may include the improved APP's interface information. An assessment of the optimization impact will be provided by the neural network (such as providing scores). In this methodology, the proposed AIAM approach (see **Fig. 4**) is more of a digital assistant, which is present in data.

*Task Evaluation*

The core components of a job may be broken down into many parts based on how they interact with each other. The availability algorithms of interface interactivity developed in this research is used to assess the availability of a job done by a user. A task's click events are initially recorded on a timeline. The retention duration of a page in a certain activity is denoted by the $R_i$ metric. The value of every click is based on Ri. In the end, we get a timeline histogram for a job. We acquire an overlapping histogram after projecting and averaging all scatter plot of the same jobs. Since of this, it is not possible to overlay histograms on top of each other, because each operation has a separate time frame. Scaling all histograms to the same extent is essential. As a result, we use a scaling projection approach to translate all timeframes to the same lengths. Scaled and combined histograms are then recorded as an array of information. Positive and negative values are used to categorize all arrays. The histogram dataset must be turned into picture data before it can be used to project all users' clicks while performing a task $T_i$ on the sites. Each click is represented by a circle with a gray value α. Divide the stay duration of each page by 255 to get an approximate idea of the gray value. It is possible to change the gray value computation algorithm to fit various neural network designs in real application.

*Optimization*

Dynamic challenges may be solved with the aid of recurrent artificial neural network systems. The design of an artificial neural network is more complex than that of Shallow Learning. Human brain activity could be segmented into behavior, self-reflection and instinct according to Lebedev et al. [27]. **Fig. 5** depicts a proposed MEM, centered on these three tiers and AIAM future technologies.

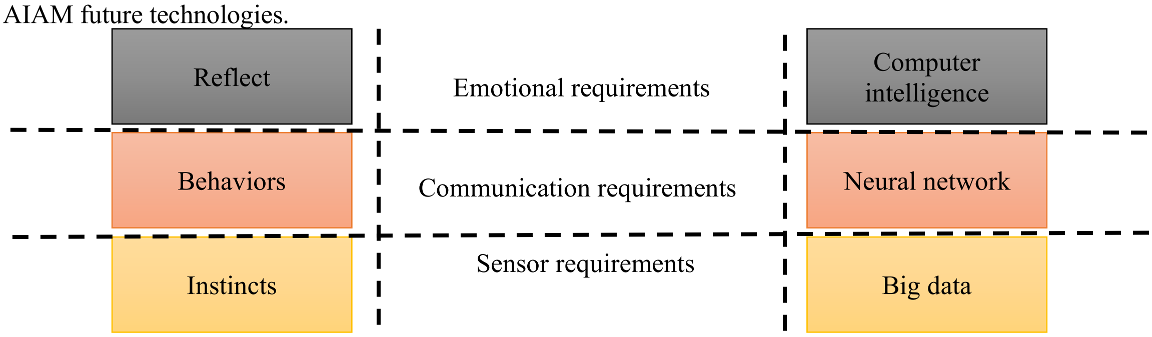


**Fig 5.** proposed MEM based on AIAM future technologies

The capacity to analyze vast amounts of data and enable deep learning is at the heart of big data, which encompasses a variety of data processing, storage, and mining techniques. The accuracy and intelligence of deep learning, which relies on enormous amounts of important data, has improved. Data, machine intelligence and neural network may be used to map the logical link between intuition, behaviour, and reflection layers by evaluating their multi-level mappings and correlation mechanisms. VGG is the neural network architecture used in this study. We chose VGG because of its basic structure and ease of implementation even by non-professionals. All of the network's convolutional kernels and pooling layers (up to 3 by 3) have the same size (3 by 3). A huge convolution layer is inferior to a composite of multiple tiny convolution layers. Maps of mobile user activity are shown on this page.

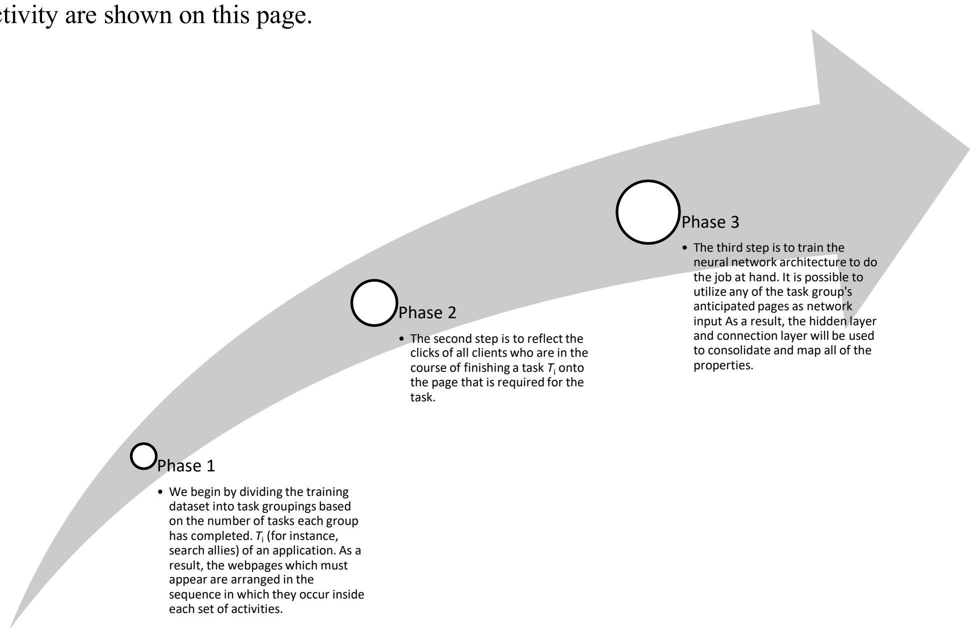


**Fig 6.** Phases involved in training an ANN

In order to develop the network framework, we employ LSTM, which has a high time attribute. When training long sequences, gradient fading and gradient eruption can occur. LSTM is an RNN that is designed to address these issues. For the processing of sequence data, an RNN is a kind of neural network. Unlike a traditional neural network, it is capable of processing data that changes over time, unlike a traditional neural network. Driven by the LSTM-CNN paradigm, we recommend to integrate the VGG core network and the LSTM system. **Fig. 6** shows the phases involved in training an ANN.

Only one output is generated by the deep neural network, which represents the score of the input data. Using data from earlier versions of the APP to train the neural network structure, the designers learn what aspects of the user experience can be enhanced based on the click behavior of actual users and then tweaks the user interface and functionality paths appropriately to produce an optimal version. An improved APP's interface may be fed into the generated neural network framework using regular operating data. Evaluation of optimization impact is provided by a neural network In this approach, the suggested AIAM solution is more a digital assistant that is in the data. The launch and upgrading of mobile applications will move much more quickly and efficiently as a result of this.

## VI. RESULTS AND DISCUSSION

*Evaluation Results*

All aspects of user engagement with a product or service are included in the term user experience. The user's experience is impacted by a variety of factors, including user-centered design, accessibility, impact design, and the technological acceptance paradigm. HCI offerings may be built using the conventional interface design method, design principles, patterns, and other techniques. Without respect to their usefulness, cognition and context awareness are frequently employed in a wide range of situations. **Fig. 7** displays the findings of the study, where a comparison between two mobile applications has been done.

We conduct a normal experiment to illustrate the usefulness of the methodologies we've supplied for evaluating the modified mobile application's functioning. 80 percent of usability issues may be discovered by doing usability testing with five to seven users. Consequently, we asked for the participation of six users, each of whom brought his or her own mobile device to the test. Three males and three girls, from various grades and majors, are part of this group of students who have expertise with mobile apps and utilize mobile social networking sites on their phones. We felt it was critical to explain to each participant in advance what they may expect from the experiment, including what data they would get on their cell phone. It took around two months to complete the whole study. The "Waterman" app had to be installed on the user's mobile phone. Detailed log data and user assessment records were gathered and archived. The tiny screen of a mobile terminal means that material can only be shown in a limited amount of space, thus it is critical to provide consumers with a comfortable viewing experience. This means that an assessment index should incorporate the aesthetics of an interface. Seven metrics were used to assess "Waterman's" usefulness, including learning, efficiency, error, interface aesthetics, and user happiness. Each participant was required to complete all activities and provide comments at least every three days throughout the assessment procedure. In the course of running the program, all data pertaining to user activity was transmitted to the domain controller and kept in log files.

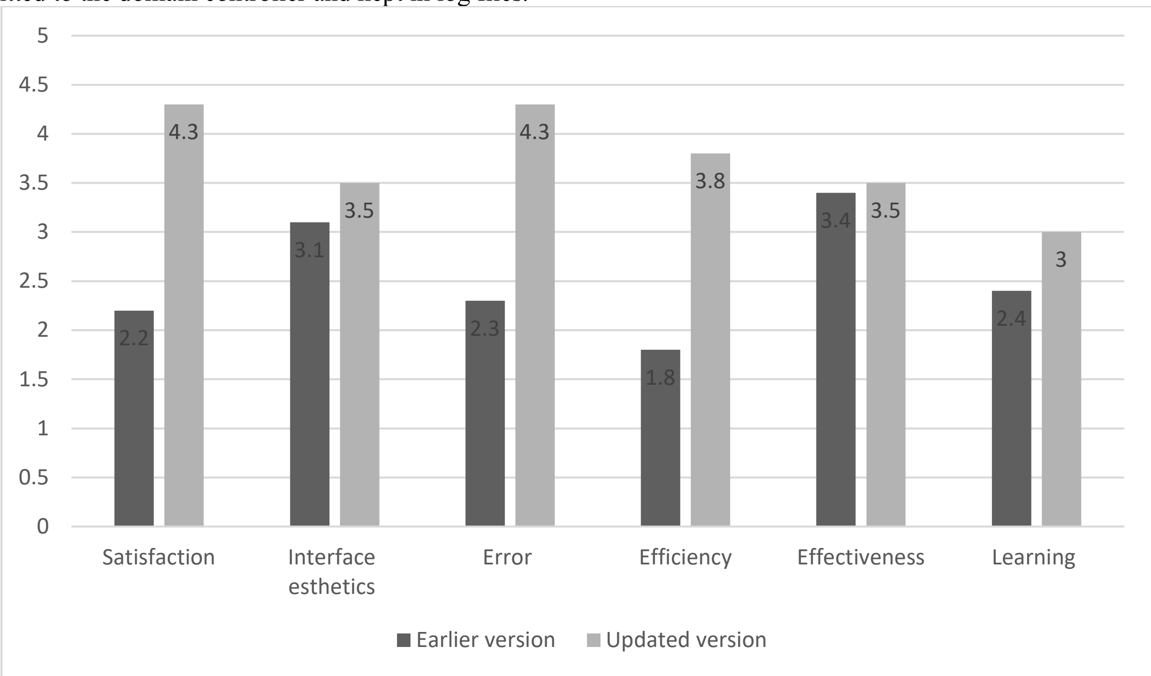


**Fig 7.** Comparison between two mobile applications

**Fig. 7** compares the two mobile applications and shows that the optimized one outperformed the non-optimized one across the board. Our suggested technique was found to be successful, notably in terms of efficiency, error, and customer happiness. Based on our research, we think that deep neural networks are better able to decipher the behavioral data of their users. A/B testing may be done more quickly and correctly with the assistance of DNN trained by the dataset from the user behaviours. Two sets of individuals were tested with two different application versions (versions A and B). Finally, the assessment is utilized to decide which version is superior. The effectiveness of optimum design has been considerably increased, according to experimental data. Our technique is distinctive in that it demonstrates causality by connecting human brainwave activity to a computer experiential representation of the data. It is our idea to employ a DNN model to measure how consumers feel about an encounter. As a result, hidden layers may be used to map all aspects of user behavior. The AIAM system has been shown to be beneficial by the evaluation outcomes. Deep neural networks, on the other hand, are unable to significantly enhance the user experience for some metrics (such as learning and efficacy). A designer can only employ AI as an assistive design tool since AI is not omnipotent.

*Challenges in Implementation of AI and ML in User Experience*

With regards to user experience, both artificial intelligence and machine learning (ML) have a lot in common. The incorporation of AI and ML in user experience, however, requires a deeper understanding of how to do so. When it comes to designing a product, it's important to break down barriers and begin with these guidelines:

(i) The first step is to establish a shared language, and in order to do so, you must first convey the business purpose and the user experience that is desired. In order to improve the user experience and develop a product outing, all AI with ML approaches with user experience must function in the same language and communicate the same principles. AI specialists and user experience developers should work together on a shared platform to create a blueprint for a fantastic user experience, which is the ultimate goal.

(ii) Even keeping historical data has gotten a lot easier because to the advancements in technology. That is why it is critical to use both descriptive and inferential statistical data in the event of an AI/machine learning convergence. Methods that allow users to emphasize certain aspects of the product may assist gather qualitative data, such as open-ended surveys, user interviews, and experimentation.

(iii) Conversely, quantitative data will reveal how the products is really utilized. As a result, user experience requirements and predictive analysis findings may be accurately assessed thanks to the availability of such sorts of data. The utilization of science alone is not sufficient if the product is very user-intensive and concentrates entirely on the customer.

*Future of AI and ML in User E*

AI and ML are playing a major role in making today's consumers utterly delighted, and it's easy to see how this is happening. When compared to firms that use traditional methods, those that use AI/ML and predictive analytics are projected to succeed 65 percent more often, according to IDC's study findings. Users should expect to see an increase in AI and machine learning in the user experience area, as any organization with data resources will not leave any loose threads if they want to stay ahead of the competition in their respective industries and markets. But that's only the tip of the iceberg; AI may uncover much more than simply auto-correction and map recommendations. It's just a matter of time until smart home helpers like Alexa become more helpful, particularly when it comes to speech apps like Amazon's Echo.

AI is the only technology that can improve the user experience, and that is a truth. Everything has become easier for both businesses and customers thanks to artificial intelligence. The bottom line is that both consumers and corporations benefit from this arrangement. AI and ML have a bright future if more people are ready to get involved and grasp how they may be used in the user experience sector. Human existence has been transformed by the rise of artificial intelligence (AI), or "machine learning." A wide range of Artificial Intelligence (AI)-enabled goods, from mobile devices to smart home appliances, make life a little bit simpler. Manufacturing, healthcare, and even security have all been taken over by AI, which is progressively finding its way into eCommerce. AI may be used to enhance a company's performance and deliver a better user experience for consumers. Unfortunately, designers are falling behind in making use of this age-old tool. A well-considered user-centered view of the future of AI intervention appears to be out of the question. There are no design patterns, prototype instruments, or design schools that integrate AI technology as a standard part of user experience design methodology at this time. It has been reported that designers of user interfaces are still ignorant about DNN, according to Chen, Qu and Gong [28].

## VII. CONCLUSION AND FUTURE RESEARCH

AI strategies for mobile communication are presented in this study as a tool for better understanding and quantifying the mobile user experience. AI technology relies heavily on machine learning and, in particular, a deep neural network. Data, neural networks, and machine intelligence are all examined in this research to see whether the logical relationships among the three layers of the brain can be deduced from their multilevel mappings and connection mechanisms. Based on user activity data, a DNN model may mimic the user experience to some degree. As a result, we advise that user log data be fully used in order to lower the acquisition costs of user behavior dataset. Using this paradigm as an assistant conceptual design may help you better comprehend the user's experience in the future, thanks to its versatility. To begin with, we would want to expand our technique to include additional user activity data, such as the ability to drag and drop. Adding data about the person, such as their profile, location, and other personal data, is a second objective of future research. Lastly, we would be modifying and improving our DNN model for correlating user mental models.

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