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Building Intelligent Adaptive User Interfaces (IAUI) With Artificial Intelligence & LLM Models.

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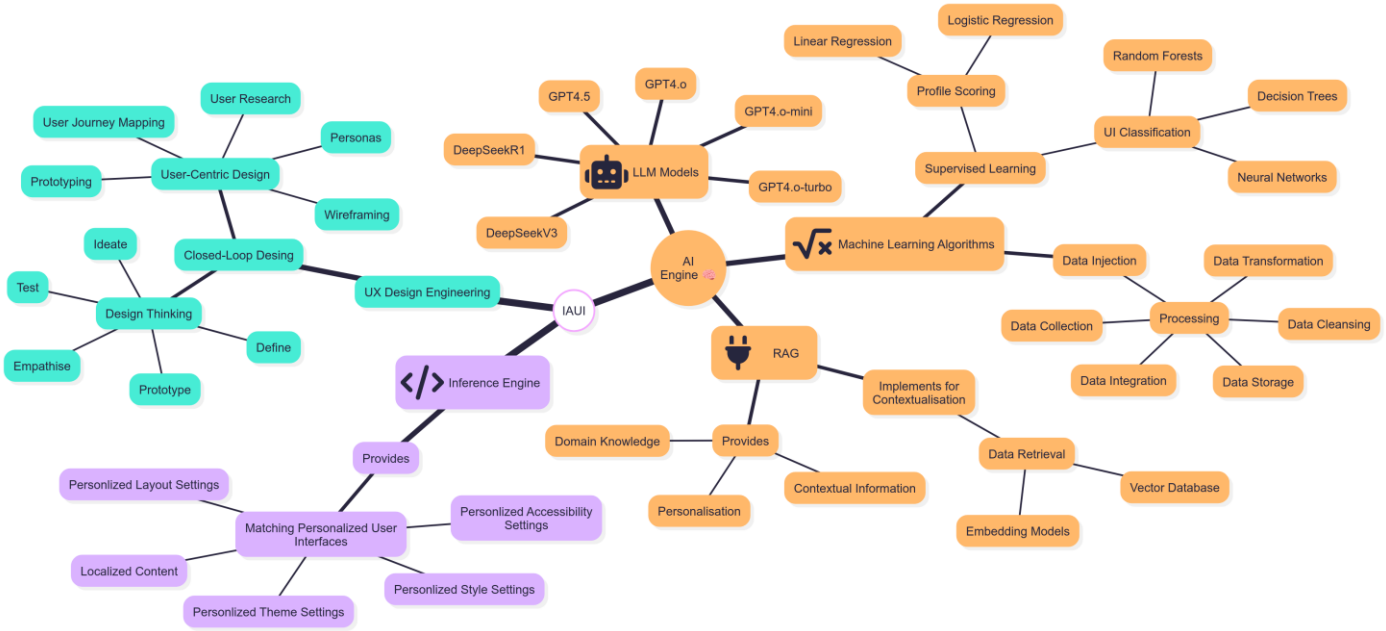

Abstract – *As the number of users leveraging online platforms over the internet is growing rapidly has created unmeasurable competition over the digital landscape demanding a need for a more personalized, intelligent and adaptive UI framework that can adjust itself based on the various factors such as user needs, environment, level of user understanding, historical usage patterns, age groups etc. to better serve the end user & provide more value for the time they are spending. All these needs demanded a revolutionary approach for building intelligent User interfaces known as Intelligent Adaptive User Interfaces (IAUI) powered by Artificial Intelligence, LLM Models & Empathy. This article will delve into the concept of IAUI, a novel framework for adjusting UI dynamically, increase user engagement, decrease the learning curve & increase accessibility in sectors such as E-commerce, healthcare, financial services, educational platforms & entertainment by using some of the pre-built LLM models using Retrieval-Augmented Generation (RAG).*

Key Words: Intelligent Adaptive User Interfaces (IAUI), Artificial Intelligence (AI), Large Language Models (LLM), Empathy, Accessibility, Adaptability, User Experience (UX), Retrieval-Augmented Generation (RAG), unsupervised learning.

1.INTRODUCTION

Over the past two decades the number of users over the internet has grown exponentially, representing a paradigm shift in human-computer interactions. In 2000, the user number were about 7% of global population (~413 million users)[1]. In 2010, it was reported to be 29% of global population (~1.9 billion users) [1]. In 2020, it went up to 60% (~4.7 billion users) [1]. In 2025, it was reported to be at 67.9% with whooping ~5.56 billion users [2], [3] across various sectors such as Healthcare, E-commerce, E-learning, Entertainment & Social media.

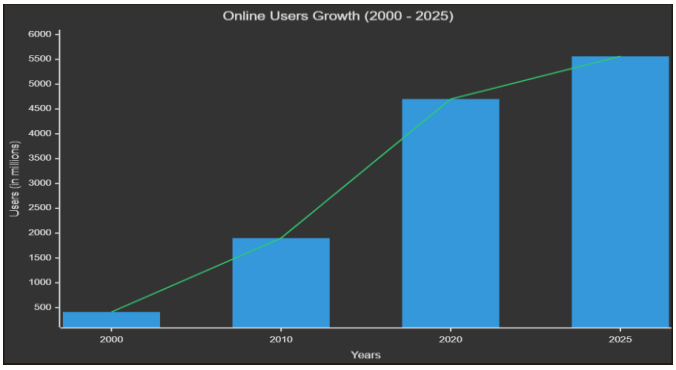

Chart -1: User Growth Chart (2000 – 2025)

This huge flux of users over the internet has created immense opportunities and unending competition for businesses to attract more customers, retain old customers, provide more value to their time spent has created inevitable need for more intelligent UIs which can not only change itself based on the screen size of the device, but also represent itself with more intuitive and tailored information based on the key factors of the user interacting with it.

If this inescapable demand was an ask decade ago, it might have been a difficult demand to meet. But over the last decade, the paradigm shifts in the capabilities of Artificial Intelligence (AI), Large Language Models (LLM), Machine Learning techniques & Computing power of Servers. Some the growth rates have been showcased below

Table -1: Computing Power Growth Rate over the past 2 decades [4], [5]

Period	Compute Power	Annual Growth Rate	Performance Milestones
2005–2010	1.1 petaFLOPs	1.5x	Basic ML models (e.g., NPLM)
2011–2015	470 petaFLOPs → 1 exaFLOP	2.3x	Image recognition error ↓73%
2016–2020	1.9 exaFLOPs → 314 exaFLOPs	4x	GPT-3 (175B params)
2021–2025	2.7 zettaFLOPs → 4 zettaFLOPs	2.3x	GPT-4 (86% MMLU accuracy)

Along with the computing power of the AI machines, the improved capabilities of user devices have made it easier and possible to inject Intelligent AUIs on to the face of users without compromising on the response times and the quality of user experience.

In This article will further delve into various User Experience Design concepts (pre-steps to IAUI), system architecture of an IAUI, real time application of the IAUI in current market, Performance metrics, Challenges and possible solutions.

2. RELATED WORK

The Adaptive User Interface concept was first discussed by David Benyon in his article about designing adaptive systems for solving usability problems [6]. As this was an early phase of research on adaptability. The paper doesn't present a solid implementation guide for creating a adaptive user interface.

According to an original research study on "Smart Product-Service Systems" a novel business approach emphasizes a key technique to design a AUI is to follow a closed-loop design to allow both customers and providers to work together in various stages of design process to build a more customized user experience meeting user needs [7]. This comprehensive study has explored how these adaptive user interfaces can be applied to multiple IOT Devices, Wending machines, Smart home devices with use of powerful custom Machine Learning Models. This paper doesn't talk about how we can use some prebuilt LLM Models which leverage unsupervised learning to build personalized intelligent user experiences.

According to another original research study on various design methodologies or techniques for creating more meaningful "User Experiences" is to use Empathic design principles powered by a powerful human emotion called empathy. An ability to feel and understand other's emotions [8]. This research emphasis the fundamental importance of empathy in design process and how to implement this technique to design more personalized "User interfaces".

We will be discussing this concept in depth in upcoming sections of the article.

2.1 Intelligent Adaptive User Interface (IAUI)

Intelligent Adaptive User Interfaces (AUI) is a powerful framework allowing user experience which is self-reliant, & can change their appearance, content, size based on various key user metrics, environment conditions, location of the user/device, device attributes etc. in real-time. Along with their self-reliance, they are also self-taught. Which means they evolve every day, every minute, every second with every user interaction. They keep learning from the data it collects, by feeding them back to the design process forming a cyclic process.

There were many techniques to develop Intelligent Adaptive user interfaces (IAUI) from design phases to inferencing. In this paper we are concentrating on using pre-trained LLM models to perform various operations in our proposed system architecture. Which we will be going over in detail in the below sections.

3. PROPOSED SYSTEM

The Proposed Intelligent Adaptive user interfaces (IAUI) system has three major components.

1. UX Design Engineering
2. AI Engine.
3. Inference Engine.

3.1 UX DESIGN ENGINEERING

UX Design Engineering plays a crucial role in designing adaptive user interfaces, which can solve a real user problem. No matter how intelligent your interfaces are, if they are not designed based on real user problems. They won't be adhered, accepted by the users. So, having a good

design system is a crucial part of the Intelligent Adaptive User Interface (IAUI) framework.

Two of the best techniques/methodologies to develop User Centric, personalized user experiences are being discussed in the further sections

1. Closed-Loop Design.
2. Empathic Design.

3.2 CLOSED-LOOP DESIGN.

Closed-Loop Design emphasizes on active participation of the end user & business directly or indirectly in different stages of User Experience design process [7]. Some examples of those stages are

1. Requirement Gathering: In this stage the end user can be the source of requirements, providing us detailed input on how a user's experience can resolve their needs.
2. Design Validation: During this stage, the designs are validated with users before any development can start.
3. POC Validation: During this stage, the end user can be our first validator providing us with feedback on how well the designs adhere to their requirements or how they deviate from them. This POC validation stage will allow us to quickly correct any mistakes, before it goes to the next phase.
4. Final Product Validation: During this stage, the end user or customer can be a validator of our deployed version of the user designs. This stage will allow them to consume them as an end user, play around with it and provide us back with more constructive feedback.

Fig - 1: UX Design Life Cycle

Following this closed-loop design process helps us to better connect with users and develop more meaningful experiences for them.

3.3 EMPATHIC DESIGN.

Empathic Design framework has been one of the best frameworks for designing User Experiences which are closer to what a user needs. The research and importance for "Empathic Design" was emphasized in a book "Empathic Design" by Koskinen & Battarbee [9]. According to it the best way to design a user experience is by understanding the user needs, having empathy towards his or her feelings, will enable us with more powerful thoughts to design something which will take us closer to the user's heart.

Over the past two decades, Empathy has become an essential component in the "User Experience Design" process for producing more human centric design bases on the real people perspectives. It also enabled designer to design solutions to problems bases on real user experiences [8].

The major characteristics of "Empathic Design" are

1. Finding equilibrium between Rationality and emotion
2. Defining end users as the source of requirements and partners in the design process along with stakeholders.

Some of the adoption and success rates of "Empathic Design" over the past two decades are shown below.

Table -2: Adoption and success rates of "Empathic Design" over the past two. [10], [11]

Period	Adoption rates	Success rates
2005–2010	~40% adoption in healthcare sectors	- 20 – 30% of reduction in redesign costs - 25% higher user satisfaction
2011–2015	50-60%	- 30% faster decision making - 40% reduction in design bias
2016–2020	65 – 70%	- 55% increase in innovation
2021–2025	75 – 80%	60% increase in user satisfaction rates

3.3 AI ENGINE

AI Engine forms the brain of the Intelligent Adaptive User interfaces which act as an Adapter between the LLM Models, and internal systems.

AI Engine is primarily built on "Unsupervised pre-trained LLM Models" to avoid "Training costs for customized models" increase availability and decrease maintenance costs for the companies.

AI Engine user data that it receives from the "Inference Engine" and system database using RAG, with system prompts to instruct LLM to perform some unsupervised learning of user key metrics to perform "Profile Scoring", "Geo-location identification", "Time Detection", "Device Information" & Built RAG Data to respond to the inference engine on which UI Component to be used for the specific user, theme to be used based on the location and time, "Content Cultures" to be used to display more localized content.

We have used three popular models (gpt-4.o, gpt-4.5, gpt-4o-turbo) to compare their performance in terms of accuracy of "Profile Scoring", "Theme detections", "UI Component Classification".

3.4 INFERENCE ENGINE

Inference Engine forms the main interaction layer between users, user interface & AI engine. Its main responsibility is to collect user data from our user stores, component libraries, location & device information, apply data transformations, aggregate the data and pass it back to the AI Engine for context awareness for further evaluation.

It is also the main layer which collects data against our users etc. to persist in our data stores.

Finally, before sending back the results it performs "Output processing" to transforms the results back to something that UI can parse & understand.

5. SYSTEM ARCHITECTURE

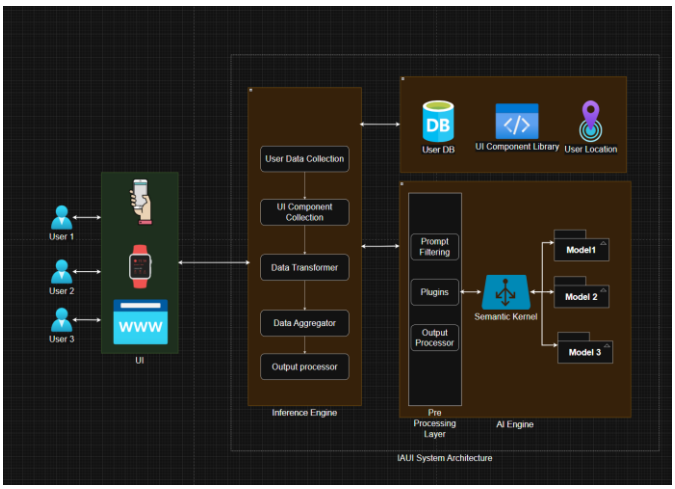

Fig - 2 IAUI System Architecture.

6. METHODOLOGIES

Our proposed "System Architecture" implements some of the below methodologies to explore the use of pre-built LLM capabilities for designing more intelligent user experiences.

1. Retrieval-Augmented Retrieval (RAG).
2. Prompt Engineering.
3. Plugins & Filters.
4. Profile Scoring.
5. Un-supervised learning.
6. Natural Language Processing & Natural Language Understanding.

"Retrieval-Augmented Retrieval (RAG)" is used to provide contextual information about the system specific attributes as the LLMs are trained with non-system specific attributes and the information it has might be outdated. So, using RAG you can provide context to it which is only specific to a system and expect a "Grounded" response from it. Without it the model might hallucinate and provide unrealistic response.

"Prompt Engineering" is used to provide some critical instructions to the LLM, such as its behavioral context, what it supposed to do, what it is not supposed to do, directions to how & from where it can retrieve contextual information using specific plugins & filters, format of input & output it supposed expect and produce. To achieve the desired results from an LLM model, having a good prompt strategy is very crucial. We have followed 3S principles for designing the prompts.

"Plugins" are the way LLM model will react with our system to perform certain custom operations, getting system data for RAG etc.

"Filters" are used to filter out any bad inputs or prompts to be fed into LLM and to filter any unexpected data coming from the LLM to save guard the system.

"Profile Scoring" – We are scoring profile based on the user features such as login frequency, login active times, age. This score is calculated by the LLM model, which is then used to correlate the user to respective UI components, categorized based on their level of usability and score bands. All this was done using pretrained LLM models without needing to train any custom models.

"Un-supervised learning" - we are using pre-trained LLM models, which are more generalized Machine learning models trained not specifically for our system. This can significantly save the custom model training, maintenance and inference costs. This outcome can boost many small to medium businesses which don't want a headache of incurring all the above costs.

"Natural Language Processing (NLP) & Natural Language Understanding" – we are using natural language prompts to instruct LLM to behave as we are expecting it to work. This technique utilizes NLP, NLU capabilities of LLM, to define its characteristics.

We will be processing our output from LLM in JSON formats.

7. RESULTS

We have performed some comprehensive testing for a sample size of 100 users, 10 sample UI components for different levels of users. The user's sample was distributed across 5 different locations with different Time Zones, different times of the day for verifying environmental awareness of the system. Below are some of the comprehensive test results across the LLM models used for the same "Test Data".

7.1 Profile Scoring

We have implemented "Profile Scoring Module" on the above test data, to categorize users into 5 categories

- 0-20: Very Low
- 21-40: Low
- 41-60: Medium
- 61-80: High
- 81-100: Very High

Table – 3: "Profile Scoring" Module results using "Random Forest Regression".

Model	Mean Absolute Error	Mean Squared Error (MSE)
GPT 4.o	2.17	6.69
GPT 4o-mini	1.94	5.82
GPT 4.1	1.9	5.34
GPT 4.1-mini	2.17	6.69

Although the precision of the result matters, sometimes when you are working bands, the response time of the LLM becomes a key factor as well. Below are the response times of the LLM models we have used so far.

Table - 4: LLM Models Response Times

Model	Response Times
GPT 4.o	2.896s
GPT 4o-mini	1.89s
GPT 4.1	1.98s
GPT 4.1-mini	1.78s

7.2 Environmental awareness:

We have tested our LLM models to recognize the user application theme based on the environmental awareness such as setting theme to "light" during daytime & "dark" during nighttime. We have fed the LLM prompts with user location, time zone, custom time plugin to fetch the current user location time based on the "IANA Time Zone".

We have tested the LLMs using 100 user samples, spread across 5 different Time Zones. We have executed the tests at different "America/New_York" time zone times to detect the theme detection behavior.

Time zones used:

- America/New_York.
- Europe/London.
- Asia/Tokyo.
- Australia/Sydney.
- Asia/Kolkata.

Test Case Execution Times:

Table - 5: Time Zone and Test Case Execution Times

Time Zone Used	Test Case Execution Time
America/New_York	9 AM
America/New_York	12 PM
America/New_York	4 PM
America/New_York	9 PM

Below are the test results by LLM model, Time Zone, Theme detected.

Table - 6: Model, Time Zone & Theme detection results

Model	Time Zone(s)	Test Result
GPT 4.o	America/New_York, Europe/London, Asia/Tokyo, Australia/Sydney, Asia/Kolkata	Passed
GPT 4o-mini	America/New_York, Europe/London, Asia/Tokyo, Australia/Sydney, Asia/Kolkata	Passed
GPT 4.1	America/New_York, Europe/London, Asia/Tokyo, Australia/Sydney, Asia/Kolkata	Passed
GPT 4.1-mini	America/New_York, Europe/London, Asia/Tokyo, Australia/Sydney, Asia/Kolkata	Passed

7.3 Localization awareness:

We have also tested the LLM models to provide the right localization information for showing the UI components in the native local languages. The response from the LLM was expected to be responded with ISO 639-1 format. We have used 5 different countries for testing this.

- Australia.
- Japan.
- India.
- United States.
- United Kingdom.

Table - 7: ISO 639-1 Language Code detection test results.

Model	Time Zone(s)	Test Result
GPT 4.o	Australia, Japan, India, United States, United Kingdom	Passed
GPT 4o-mini	Australia, Japan, India, United States, United Kingdom	Passed
GPT 4.1	Australia, Japan, India, United States, United Kingdom	Passed
GPT 4.1-mini	Australia, Japan, India, United States, United Kingdom	Passed

7.4 Component Profile Mapping:

We have tested the LLMs ability to correlate calculated user profile scores with the UI components for loading various skins of the UI to make it more usable, easy to understand and navigate for the end user. We proactively rated the UI component usability score into 5 categories.

- 0-20: Very Low
- 21-40: Low
- 41-60: Medium
- 61-80: High
- 81-100: Very High

LLMs has performed relatively well in mapping the UI components to the right set of users. Below are some of the test results. With fine tweaks to the prompt, it will be possible to achieve 100% results with LLMs.

Table 8: LLM Profile-UI component Mapping Results

Model	UI Components	Test Result (%)
GPT 4.o	<basic-navigatio> <advanced-navigation> <mid-level-card> <advanced-card> <basic –card>	95%

GPT 4o-mini	<basic-navigatio> <advanced-navigation> <mid-level-card> <advanced-card> <basic –card>	93%
GPT 4.1	<basic-navigatio> <advanced-navigation> <mid-level-card> <advanced-card> <basic –card>	96%
GPT 4.1-mini	<basic-navigatio> <advanced-navigation> <mid-level-card> <advanced-card> <basic –card>	95%

8. DISCUSSION

This section of the document will discuss more about our findings by using pre-trained LLM models to solve some of the challenges related to using custom trained models, limitations of using LLM models, challenges of using LLM Models & possible solutions to some of those challenges. We will be also discussing about the future of Intelligent Adaptive user interface (IAUI) to build "Generative UI"

Performing a comprehensive Design Study for UX design is out of scope of this article. We have provided some of the concepts we recommend for designing User Experiences. Testing them is out of scope of this article.

8.1 Challenges & Possible Solutions

"Hallucinations" - LLM models are known to hallucinate, when providing responses. The possible solution to it is to reduce "temperature", "top" parameters. Along with it providing strict guidelines with "System Prompts", "Contextual Data" with RAG will help it to not hallucinate.

"Bias Removal" - As the LLM models are trained with generalized data, to avoid bias from your system. You should be making sure implementing custom bias techniques using pre and post processing filters to remove "Bias" completely from the system.

"Token Limitations"- although LLMs can work on prompts & RAG. They have token limits, which doesn't allow you to send too much data to it. This limitation can create inaccurate results. Some of the techniques to overcome these problems are

- "Truncation" – Truncating from start or the end of the sentences to meet the token limitations. The problem with this is that it can lose context and can still create inaccurate results
- "Chunking" – Breaking down the information into smaller chunks, which will help to be processed independently and within the token limitation. "Chunking" can be done semantically to not loose contextual information.
- "Summarize" – Summarize the lengthy information into more precise sentences without loosing their contextual information. This can drastically reduce the amount of information you are sending to LLM.
- "Remove Redundant Terms" – Removing redundant terms such as stop words, will also reduce the amount of information being fed to LLM.

Depending on the use case you might end up implementing one or more above techniques to keep the information shared within the token limitation boundaries and yet achieve more precise results.

"Scaling" – As the user base increases, the number of times we perform these "Profile Scoring", "Component Mapping", "Environment awareness" using LLM models increases as well. So, soon we will get into a position where the system needs to be scaled. One solution, As the LLM models are managed by the third-party providers on their cloud systems, they can easily scale and we can buy more dedicated equipment to run the models from the cloud providers such as Azure, AWS etc. Another solution is to acquire powerful machines on prem or on cloud (VM) & deploy LLM models locally. This allows us to control over when to scale up and scale down, staggering model updates etc.

"Data privacy" – LLM models are used by many applications across the world. To avoid it sniffing into your data for its training. You should be implementing safety measures at the model provider level as well as in the application to redact PII information & any other personal information from the data being shared to LLM. This might impact the accuracy of the model, but to not effect the accuracy of the response, we can share it as "contextual information" up on when the LLM model needs it before providing final response.

"Prompt Creation" – Producing a right prompt is a very crucial step for integrating with LLM model and get the right information out of it. Creating Prompt is an iteration process and might take a lot of time to produce the right prompt that will work for your use case. There as some great "Prompt Engineering" principles to help us create a powerful prompt. One of the most used and great principle is "3S Principle" to craft better prompt. [12]

8.2 Advantages of using prebuilt LLM Models

As we know, how powerful the LLM models can be and how they can help us achieve building more modular and adaptive interfaces. To create or train a custom model, we

need a lot of manpower and compute power. Below are some of the Training costs of some of the popular LLM models.

Table - 9: LLM model training costs. [13]

Model	Parameters	Training Cost	Key Factors
GPT 3	1.75B	$4.6 milion	NVIDIA V100 GPUs
GPT 4	1.8T+	78-100 million	Specialized hardware (H100 GPUs)
Falcon 7B	7B	30K – 450K	GPU fine tuning

Table 10: Maintenance & Serving Costs. [14], [15]

Model	Deployment	Monthly Cost	Components
Falcon 7B	On-demand GPU	1.006/hour(724/month)	Single NVDIA V100
Llama3-8B	AWS (g5.2xLarge)	872-1745	Single-node GPU, autoscaling
Llama3-70B	AWS (ml.p4d.24xlarge)	$27,360	Specialized hardware (H100 GPUs)

Many smaller and medium-scale organizations would find it hard to train & maintain LLM models on their own because of the cost associated. Which takes out an opportunity for them to build Intelligent User experience.

But with the use of prebuilt LLM models, they can drastically reduce the costs to only inference costs, & cloud providers are providing various payment plans to fit the organization needs, which can enable every organization to leverage the beauty of artificial intelligence into their user experience.

8.3 Real Time Applications:

Building Intelligent Adaptive User interfaces has already taken its shape by many major organizations building various intelligent modules using Custom Machine Learning Models. Below are some of the instances of those by their functionality.

Table 11: Real Time IAUI implementations. [16], [17], [18], [19]

Functionality	Improvement (%)	Organization
Recommendation systems	40% of user retentions from amazon, 75% of user engagement increases by Netflix. 30%	Amazon, Flipkart, Shopify, Netflix
Profile Level & Paced learning	14% user retention,	Duolingo
Environmental Awareness	30% user engagement increase	Google Maps
Intelligent Chat Bot	40% decrease in customer care cases.	Amazon
Personalized Playlists	40% increase in User engagement	Spotify

9. CONCLUSIONS

Intelligent Adaptive user interfaces (IAUI) provide a new paradigm for more personalized user interfaces increasing, user engagement, improving accessibility & efficiency of the systems. Although they provide great opportunities for businesses to take them closer to the user's needs. They come with their own challenges related to data privacy, development & maintenance costs, design complexities, high computer equipment & data collection. With the use of pre-trained LLM Models. There might be a chance of not meeting customers' needs as they are vast and have been trained for multiple use cases. One possible solution to this challenge is to use custom trained "Small Language Models". Which are trained for specific use cases to not

In many cases the potential benefits of implementing IAUI outshine its challenges, especially for many well-established companies, which have enough resources to spend on them.

Finally, IAUI paves the way for more powerful "Generative UI" to achieve complete autonomy on designing, building & maintaining personalized UIs, blurring the line between design & UI [20]

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BIOGRAPHIES

Innovative Enterprise Applications architect | Microsoft certified professional (MCP) | AI Engineer trying to create novel solutions to hard problems using Artificial Intelligence.