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THE USE OF ARTIFICIAL INTELLIGENCE IN ADAPTING PROCESS OF UI DESIGN SYSTEM FOR END CUSTOMER REQUIREMENTS

This paper demonstrates an approach for developing an AI-based UI design system to improve a company white labeling (aka rebranding) process. This is the process of removing a product or service's original branding and replacing it with the branding of another company or individual. The main objectives of the research include the development of methods for optimizing rebranding, automating the delivery of designer work results, and achieving project-wise improvement in the design adaptation process for the end distributor, known as the white-labeling process. The research objective is to analyze the existing rebranding process and to analyze ready-made solutions using artificial intelligence to improve it. This research identifies innovative methods for implementing artificial intelligence in the rebranding process to facilitate and speed up tasks related to design and marketing. Research methods include analyzing existing rebranding practices, considering ready-made solutions using artificial intelligence, and conducting experiments and practical application of new methods to improve the process. The scientific novelty of this research lies in the implementation of artificial intelligence in the rebranding field and the development of effective methods for its improvement. As a result, improvements are achieved through the deployment of an AI-driven solution, meticulously engineered around the design token concept, serving as a pivotal element for standardizing and harmonizing the work of designers. This methodology involves a comprehensive adjustment of the AI model to seamlessly integrate with existing design systems, thereby facilitating the transformation of design systems and brand books into tangible design tokens. The process of integrating AI into design workflows involves extensive model training using openly accessible community data. Careful consideration is given to the selection of datasets, ensuring that they meet rigorous criteria for evaluating the quality and efficacy of artificial intelligence learning. These criteria encompass factors such as data relevance, diversity, and representativeness, as well as considerations for ethical and legal compliance. As a conclusion: by leveraging this meticulously crafted approach, organizations can effectively harness the power of AI to drive transformative change in design processes, ultimately enhancing efficiency, consistency, and innovation across their operations. By adopting various AI integration aspects, this paper provides an updated UI design process with the ability to use AI during client-centric design development.

Keywords: *design tokens; artificial Intelligence (AI); design adaptation; system design; white labeling; AI-driven adaptation; customization; design automation.*

1. Introduction

1.1. Motivation

In the rapidly evolving field of information technology, artificial intelligence (AI) is playing an increasingly significant role in various industries, including design and marketing. One of the most promising applications of AI is the rebranding of design systems, where AI can optimize workflows and address challenges that complicate the process (Fig. 1).

The traditional rebranding process involves gathering requirements, conducting brand research, iterative design, updating design tokens, testing, and collaborating with developers. However, this workflow faces several persistent challenges. First, design tools such as Figma or Sketch, which are excellent for prototyping and collaboration, remain separate from development workflows. This creates a “black box” where design and development operate independently, leading to inefficiencies, communication gaps, and misalignment between teams. These inefficiencies often result in scope creep, delayed timelines, and dissatisfaction among stakeholders.

In the context of modern design systems [1], design tokens play a crucial role as building blocks that define and maintain the visual identity of an application. These tokens encapsulate reusable values such as colors, typography, spacing, and motion, enabling consistency across platforms and adaptability to diverse branding requirements [2]. For instance, a token like color-primary might map to a specific color code, ensuring

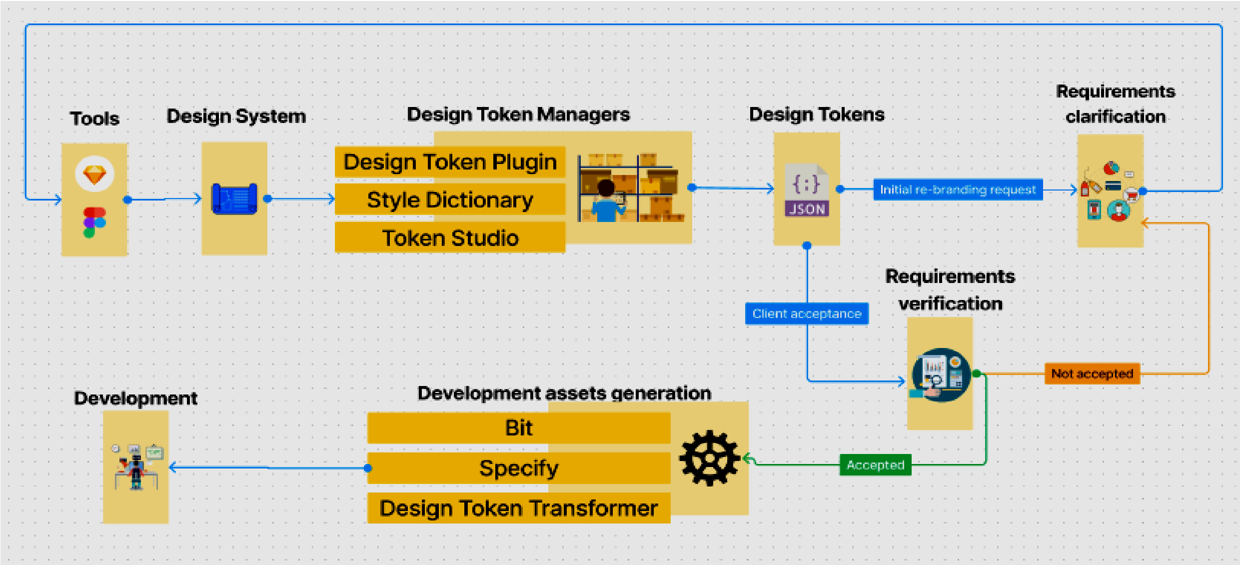

Fig. 1. Process design system development and adaptation without AI enhancement

its consistent application throughout the design system. Stored in JSON format, tokens can be easily parsed and integrated into development workflows. By managing tokens through tools such as Style Dictionary or Figma Token Studio, designers and developers gain a centralized mechanism to organize and share these critical components. Despite their utility [3], the manual creation and maintenance of tokens remains labor-intensive, particularly when scaling to accommodate multiple white-label products. This is where AI can revolutionize the process by automating token generation, ensuring accuracy, and enabling dynamic updates that seamlessly reflect brand changes.

The following article explores these issues in detail, highlighting the challenges faced in user experience, technical constraints, testing, communication, and resource management. This provides an overview of the current state of the art in design systems and delves into the current white-labeling process. In addition, it introduces metrics for evaluating AI-based workflows, stages of AI implementation, the data labeling process, and a practical case study (Fig 2). In contrast, color-text-button-discovered = purple800 would be a typical token because the naming makes it clear that it represents the color and is intended to be used for backgrounds.

With design tokens, designers can adapt styles to different platforms, rapidly iterate designs, and maintain accessibility compliance. They make theming and versioning easy, thereby enabling efficient and reusable design components. In the next example, design tokens for colors, typography, spacing, and breakpoints are presented. The key-value pairs define specific styles, such as primary and secondary colors, font size and weight, spacing values, and responsive breakpoints. It has a two-level structure.

While the rebranding process is time-consuming and error-prone, AI can significantly improve existing design systems and processes by resolving challenges related to user experience, technical, testing, communication, cost, and resources.

```
{
    "colors": {
        "primary" : "#007bff",
        "secondary" : "#6c7579",
        "background" : "#f8fofa"
    },
    "typography": {
        "fontFamily": "Helvetica, Arial. Sane-serial",
                                 "fontSize": "10px",
        "fontHeight": "1.5",
        "fontWeight": {
            "regular": 400,
            "bold": 70
        }
    },
    "spacing": {
        "small" : "8px",
        "medium" : "16px",
        "large" : "24px"
    },
    "breakpoints": {
        "smallScreen" : "480px",
        "mediumScreen": "768px",
        "largeScreen": "1094px"
    }
}
```

Fig. 2. Design token example transformed to JSON

Rebranding design systems involves challenges in terms of user experience, technical execution, testing, communication, and resource management. Ensuring consistency while accommodating client-driven changes can compromise brand identity; however, AI can analyze guidelines, suggest compliant designs, and refine usability through simulated user testing.

Technically, customization requires robust infrastructure, increasing complexity, and risk. Design tokens simplify this process, and AI can automate token creation and updates to maintain consistency across products. AI also supports scalability and optimizes

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performance while addressing design limitations and ensuring seamless updates.

Artificial intelligence streamlines the testing process by automating the generation of test cases, which significantly reduces errors, resource consumption, and time requirements. Additionally, it improves collaboration and communication by providing visual prototypes and tailored client training materials, which help clarify design intentions and minimize project delays. By automating repetitive and time-intensive tasks, AI not only reduces costs but also facilitates seamless, efficient customization, effectively addressing critical challenges associated with rebranding processes.

1.2. State of the Art

Several approaches have been proposed that emphasize key trends in artificial intelligence and address the associated challenges.

The article [4] presents the result of analysis of the current state of AI-based design and how it may improve design. According to this article, future trends include the integration of predictive design and emotional intelligence. However, challenges such as data privacy and biases must be addressed. This article emphasizes the collaboration between designers and artificial intelligence to optimize user-centric design outcomes. This article discusses the future of pure AI-generated design and the role of designers in this case.

However, AI can be used not only for generations-from scratch. This is how Uizard and Airbnb’s Design AI [5] were used to verify that the UI is correct according to user experience and intelligent to adopt cyber risks.

Another aspect of AI and designers’ collaboration using Explainable AI is described in [6]. This article discusses ways of interaction based on gathering and refining UI-related questions. This approach can be applied to multiple areas where development and interactive design are needed. The result of AI generation, given that the design shows a high level of quality, may be used as a sketch or markup for further development.

Given papers show useful and diversified ways of using AI for design generation, designers help. [7]. Unfortunately, all these approaches do not consider using AI as a part of continuous development. It is better to consider the design process as a part development process that is tightly connected to the result. In addition, a gap that is not covered by these studies is designing and development continuation and alignment. Using AI in these modes requires additional instruction and/or collaboration with an AI specialist.

In the context of rebranding [8], AI tools are being leveraged to analyze market trends, consumer behavior, and competitor strategies, providing valuable insights to inform the evolution of brand identity. By harnessing machine learning algorithms, designers can optimize brand messaging, visual aesthetics, and market positioning to resonate more effectively with target audiences. Additionally, AI-powered sentiment analysis tools enable brands to gauge public perception and sentiment toward rebranding efforts, thereby facilitating data-driven decision-making and risk mitigation.

1.3. Problem statement

This article emphasizes the importance of collaboration between designers and AI to achieve optimal user-centric design outcomes [9]. Designers play a crucial role in guiding AI systems, setting design goals, and ensuring that AI-generated designs align with the brand's vision and user needs. The synergy between human creativity and AI between human creativity and AI-driven automation can lead to effective design solutions.

Overall, the integration of AI into design systems represents a paradigm shift in the field of design [10], offering unprecedented opportunities for automation, optimization, and creativity enhancement. As AI technologies continue to evolve, increasingly profound synergies are anticipated between AI and design systems, facilitating the development of intelligent, adaptable, and user-centric design solutions.

AI and design tokens can play a significant role in addressing the challenges associated with designing a customizable white-label product that meets a client’s brand requirements [11].

The paper [12], we provide an updated UI design process with the ability to use AI during client-centric design development. The aspects of enhanced development and integration processes from the perspective of establishing new boundaries in system adaptability are considered in this paper.

Despite the variety of approaches to solve the existing challenges, the use of AI to optimize the rebranding process is still “grey” area that needs to be addressed [13].

1.4. Objectives and approach

The purpose of this study was to explore the possibilities of using artificial intelligence to simplify the application rebranding process. The main objectives of the research are to develop effective methods for optimizing rebranding, automating the delivery of designer work results, and achieving economic improvement in the design adaptation process for the end distributor.

The research objective is to analyze the existing rebranding process and to analyze ready-made solutions using artificial intelligence for optimization and improvement. This research aims to identify effective and innovative methods for implementing artificial intelligence in the rebranding process to facilitate and speed up tasks related to design and marketing.

In accordance with the research goal, it is necessary to solve the following tasks: development of AI-based design flow; adjustment of AI model to work with design systems; development of data labeling process; development of brand books and design systems for populating datasets; selection of criteria for evaluating the quality of AI learning; process improvement rating selection; and performing a case study to demonstrate the use of AI-based design flow for application development.

Research methods include analyzing existing rebranding practices, considering ready-made solutions using artificial intelligence, and conducting experiments and practical application of new methods to improve the process. The scientific novelty of this research lies in the implementation of artificial intelligence in the rebranding field and the development of effective strategies for its optimization and improvement.

The structure of this paper is as follows:

Section 1 discusses the motivation behind the study, provides an overview of related work, and presents a state-of-the-art analysis of the latest ideas and methodologies in AI-based design flow development, including their advantages and limitations.

Section 2 describes the development of the AI-based design flow, including critical aspects such as metrics for evaluating AI processes, implementation stages, data labeling process, criteria for assessing AI training quality, and the selection of a process improvement rating system.

Section 3 presents a case study that illustrates the application of the AI-based design flow to the development of a rebranded design system, offering practical insights.

Section 4 highlights the key insights and implications derived from implementing the AI-based design flow and discusses its impact on the design process.

Section 5 concludes with a summary of the findings and provides recommendations for future research directions.

2. Methodology

The development process of a white-label application includes several manual steps. These steps involve redesigning a design system to meet the specific requirements provided by the customer, developing a new set of design tokens, and transforming these design tokens into development artifacts that serve as the building blocks of the application.

AI-based processes can be constructed around design tokens, employing them as both input data and outcome indicators. By analyzing design tokens, the AI system can extract valuable insights into user preferences and market trends, enabling businesses to make data-driven decisions. Furthermore, leveraging design tokens as income data can enhance financial forecasting and revenue optimization strategies, ultimately leading to more efficient and profitable operations.

The new process incorporates the automatic transformation of brand book requirements into a computer-understandable format. In addition, it facilitates the use of design tokens and automatically generates a new set based on the requirements and initial tokens provided by the designer.

It is evident (Fig. 3) that these steps use artificial intelligence. One such step, referred to as "AI requirements transformation," employs the initial design system, the incoming brand book, and AI model to transform these elements into what are called semi-design tokens. These tokens represent all changes required in the application design. The subsequent step, "Design tokens generation," carries out the actual generation of design tokens to be used in the generation of development artifacts.

Using design tokens within the CI/CD process streamlines and enriches the white-labeling procedure, providing a systematic and effective method for tailoring design elements. This facilitates uniform and expandable branding customization, simplifying the delivery of personalized products or services by white-label providers that match the distinctive identities and branding standards of their clients.

By incorporating AI into the design system rebranding process, designers can benefit from increased efficiency, data-driven decision-making, and more creative exploration [14].

Here are some suggested ways AI can enhance the rebranding process:

Design Token Optimization: AI algorithms analyze existing design tokens and propose optimized combinations of colors, typography, and other design attributes that align with new branding guidelines. This streamlines the process of updating the design tokens to match the rebranding.

Design System Auditing: AI will conduct comprehensive audits of the current design system to identify all design elements and patterns. This step helps designers gain a complete overview of the design system and ensures that no elements are missed during the rebranding. Design and Development Collaboration:

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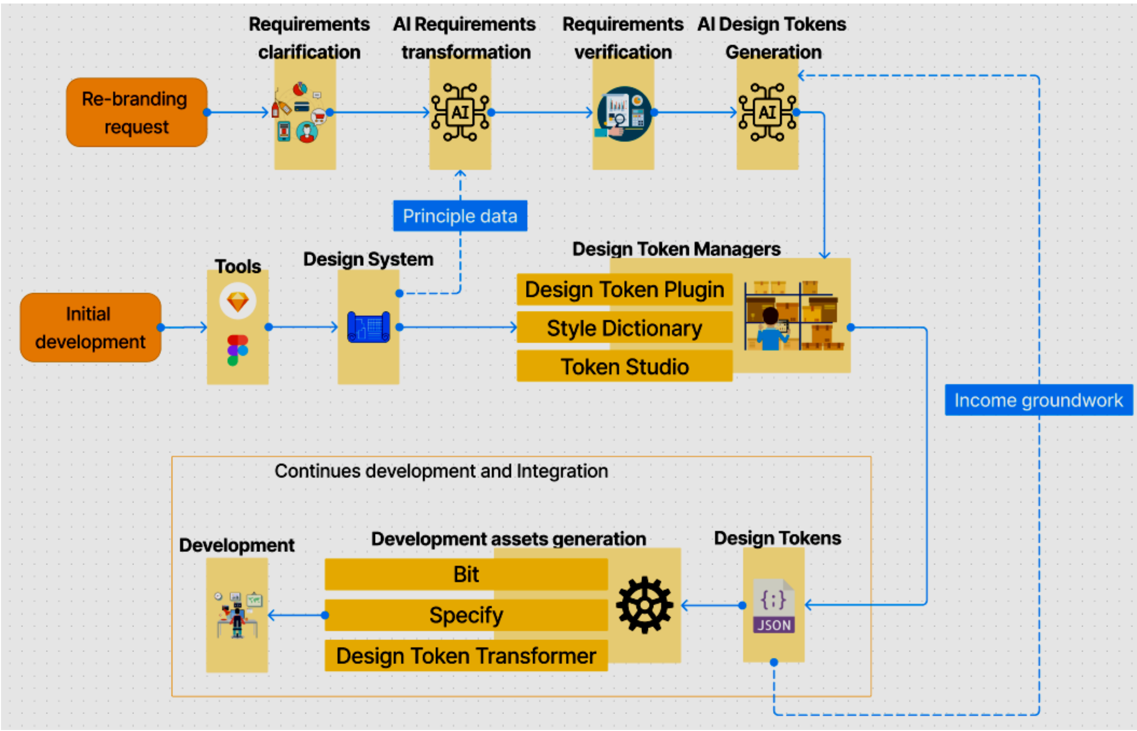

Fig. 3. Process design system development and adaptation with AI enhancement

AI-powered collaboration tools will facilitate smoother communication between designers and developers. These tools can automatically update design tokens in the codebase, ensuring that design changes are implemented accurately and efficiently.

Automated Design System Documentation: AI will assist in generating comprehensive design system documentation, including style guides and component specifications. This reduces manual documentation efforts and ensures that documentation remains up to date.

AI-powered tools help streamline various aspects of the rebranding workflow, empowering designers to deliver impactful, cohesive design systems that align seamlessly with new branding guidelines.

Several supplementary applications that provide efficient design tokens management for white labelling such as DesignTokenFigmaPlugin, TokenStudio, and Style Dictionary.

The DesignTokenFigmaPlugin is a valuable extension of Figma, providing designers with a solution to manage design tokens in their design projects. This plugin facilitates the creation, organization, and application of design tokens across various design elements.

TokenStudio is a specialized application designed explicitly for managing design tokens. This platform offers a centralized repository for defining and controlling design attributes such as colors, typography and spacing. TokenStudio enables efficient collaboration between designers and developers by serving as a single source of truth for the design system.

Style Dictionary is a versatile tool that allows teams to generate and maintain design tokens for multiple platforms and programming languages. It allows designers to define design attributes structured and generates platform-specific stylesheets, code snippets, and other resources automatically.

While these applications offer multiple means for design token management, they may not be fully integrated with the [15] CI/CD process to transform design tokens into final development resources, such as components for various frameworks.

At this stage, establishing an interconnected framework of applications and tools is essential to efficiently transform design tokens into finalized development resources that can be seamlessly integrated into developers' projects [16]. To accomplish this task, three applications were identified that will play a significant role in this process: Bit, Specify, and DesignTokenTransformer:

Bit offers powerful component-driven development capabilities. This tool transforms design tokens within components, making them easily accessible and reusable across different applications and frameworks.

Specify that this application becomes the single source of truth for design tokens, empowering teams to work cohesively while maintaining a well-documented and versioned design system.

DesignTokenTransformer is a specialized application that converts design tokens into platform-specific stylesheets, code snippets, and other essential resources.

Due to the use of Bit, Specify, and DesignTokenTransformer, the design token workflow can be improved significantly.

When executed effectively, this process not only facilitates seamless and efficient collaboration between designers and developers but also establishes a robust framework that ensures consistency, scalability, and long-term maintainability within the design system. By streamlining workflows and enhancing integration, this approach lays the foundation for sustainable and adaptable design practices.

3. Development of AI-based design flow

3.1. The metrics for AI-based flow evaluation

This AI-based flow also allows us to use metrics to estimate the quality of solutions related to user experience.

These metrics include the Brand Alignment Score, which evaluates how well the AI-generated customization suggestions align with the client's brand guidelines. In addition, client satisfaction surveys gather feedback from clients about the effectiveness of AI in maintaining brand identity and consistency.

Usability Testing Results compare the AI-customized product to manual methods by measuring task completion rates, time on task, and user satisfaction. Users' Feedback on the ease of use and overall experience of the AI-customized product.

This flow also incorporates metrics to estimate the quality of solutions related to technical challenges:

These metrics include measuring Development Time to determine the time saved in development and implementation using AI-generated design tokens and assets. In addition, Code Quality is assessed in terms of readability, efficiency, and adherence to best practices. The number of Design Iterations required to achieve desired customizations was compared with and without AI assistance. The Update Frequency measures how often AI-driven updates are applied to customized elements compared to traditional manual updates. Bug and Issue Tracking monitors the number and severity of bugs or issues related to AI-generated updates. Performance metrics measure product performance under different customization scenarios to ensure AI-optimized performance.

The AI-based flow also incorporates metrics to estimate the quality of solutions related to testing challenges:

The Automated Testing Efficiency measure includes determining the time saved in testing using AI-generated test cases and automation. The Defect Detection Rate was also compared between manual and AI-driven testing approaches.

The AI-based flow also incorporates metrics to estimate the quality of solutions related to communication challenges.

It involves measuring User Onboarding Completion to gauge the completion rate of user onboarding and training materials generated by the AI solution. In addition, User Support Requests are monitored to track issues related to customization and onboarding. Collaboration Efficiency is measured by assessing the time taken to iterate and finalize design customizations using AI-generated prototypes and collaboration tools. Improvements in the Design Review Process are evaluated, such as faster decision-making and reduced back-and-forth communication. The volume of Customization Requests was tracked and compared with historical data to assess the impact of AI-driven customization recommendations. In addition, Feature Adoption is measured by comparing the adoption rate of AI-suggested features with that of non-AI suggestions.

The AI-based flow also incorporates metrics to estimate the quality of solutions related to cost and resource challenges:

This includes quantifying Resource Utilization to determine the reduction in resources (time, manpower, etc.) required for development, maintenance, and support using AI-driven solutions. In addition, Cost Savings are calculated based on increased efficiency and reduced customization-related expenses.

3.2. Stages of AI based flow implementation.

An important step in the initial stage of AI-based flow implementation is selecting input data. At this stage, data can be filtered using qualitative characteristics such as curation, representativeness, and class balance.

Curation in the context of data and content refers to the process of selecting, organizing, arranging, and presenting information with the aim of creating a valuable and meaningful dataset or content for the audience. This process requires the curator to determine which data or content is most important, interesting, or useful for a specific audience and to meet specific needs or goals.

The curator is responsible for collecting, analyzing, and organizing information from various sources to maximize its relevance and value for the intended audience. In the context of art, this may involve selecting and arranging artworks for an exhibition that best represent a specific theme, style, or historical period.

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Representativeness refers to how well a training or test dataset reflects the reality or characteristics of the target problem. Data representation is an important aspect to ensure that the model or research can generalize and draw justified conclusions. For instance, when creating a model to forecast housing market prices, the training dataset should be representative, meaning it should reflect the diversity of factors influencing housing prices (such as house size, location, year of construction, etc.) and the diversity of real estate markets. Thus, curation and representativeness are crucial aspects in working with data because they ensure the quality, value, and reliability of information for further use in research, models, or other projects.

Each user must have unique preferences and needs. The selection of input data should reflect the variety of possible scenarios and real conditions of product or service usage.

Class balance: Ensuring an adequate number of examples for each class helps avoid biases and ensures model objectivity. The use of the F1-score is particularly important in the presence of imbalanced classes.

The next step involves data selection for testing using clustering methods. In the context of health-brand books, clustering can be used to group elements, components, or styles that are part of the health-brand book. This allows artificial intelligence to systematize and organize various elements of the brand book to improve understanding.

The key aspects are as follows:

Group colors used in the brand book and create separate palettes for different brand aspects, such as the logo, interface elements, and advertising materials.

Separating fonts and styles into different clusters and defining their use for different parts of the brand book: headings, texts, logos, etc.

Grouping graphic elements and logos into separate categories based on functionality and purpose.

Clustering design elements and layouts can organize various design elements and layouts in a brand book, separating them by stylistic decisions and using them for different types of materials. Using the clustering approach in selecting a brand book as input data for training artificial intelligence models helps create a systematic and logical structure, which makes it easier for the model to be further used.

The final step is model training. For successful training, it is important to follow these rules:

Training data volume: The larger and more diverse the training environment, the better the model can understand different contexts and respond to different situations. However, excessive data should be avoided because they can lead to model overfitting.

This method involves initially gathering a diverse range of brand books representing various industries and styles. Next, we employ clustering algorithms to group similar brand books together based on their content, design, and target audience. Once the clusters are formed, experts can label each cluster meticulously with relevant attributes, providing effective guidance for training AI models.

3.3. Data labeling process

The data labeling process is a prerequisite for model training. Data labeling involves experts or annotators assigning labels or tags to each data element in the training dataset. In the context of facial recognition, this process may involve identifying and marking each face in an image with its specific location and associated characteristics.

The role of data labeling in model training is to provide the model with correct and adequate input data for learning. The quality of data labeling affects the effectiveness and accuracy of model training because incorrectly labeled data can lead to incorrect conclusions and decisions. There are following datasets for the brand book:

Color Classification and Annotation: The primary colors that characterize a brand are identified. Annotate your images or data with colors according to the brand book. In addition, consider variations and color combinations that may be used in different contexts.

Fonts and Typography: Use text elements and fonts from the brand book to create annotations and populate textual data. Maintain text style so that the model can learn to generate or recognize text in accordance with the brand. Logos and Graphic Elements: We included logos and graphic elements from a brand book in the training dataset.

Logos and Graphic Elements: We included logos and graphic elements from a brand book in the training dataset. Annotate their location and size of images or other media files are annotated to train object recognition models.

Background and Surroundings Processing: If the brand book specifies specific backgrounds or environments for images, add these contextual elements to your dataset. This is important for a model that must work in a specific context.

Combinations and Styles: Different combinations of elements from the brand book were created to generate diverse examples in the dataset. This includes different combinations of colors, fonts, logos, and other graphic elements.

Text and Graphic Guidelines: If the brand book includes guidelines or styles for creating textual or graphic materials, use them as a direction to populate the dataset and train the model to emulate these styles.

Therefore, the model training and data labeling processes are key stages in the development and improvement of machine learning and deep learning algorithms. These stages require care, a methodical approach, and significant expert knowledge to ensure efficient and accurate artificial intelligence models.

3.4. Selection of criteria for evaluating the quality of artificial intelligence learning

The evaluation of AI model performance considers various aspects. Common metrics include accuracy, precision, recall, F1 Score, confusion matrix, ROC Curve (Receiver Operating Characteristic curve) and AUC (Area Under the Curve), task-specific metrics, time and resources assessment, cross-validation, and real-world validation. For further analysis, the F1 score and ROC metrics will be analyzed. The F1 Score can handle imbalanced datasets, whereas the receiver operating characteristic curve evaluates model effectiveness regardless of class distribution. The F1 Score combines the precision and recall information of the model

$$\begin{aligned} &\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}, \\ &\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}, \\ &\text{F1 Score} = \frac{2}{\text{Precision}^{-1}+\text{Recall}^{-1}}, \\ &\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}}, \end{aligned} \tag{1}$$

where TP – correctly identified positive results; FP – Incorrectly identified positive results; TN – Correctly identified negatives; FN – Incorrectly identified negatives.

The F1 Score balances precision and recall and is used where it is necessary to consider both aspects – the quality of identifying positive examples and their interactions within the entire dataset.

There are situations where precision and recall are mutually exclusive, and maximizing one may lead to a decrease in the other, creating a trade-off. The F1 Score addresses this issue by combining precision and recall into a single harmonic mean, offering a balanced evaluation of classification performance. This makes the F1 Score particularly valuable when dealing with small data volumes or imbalanced classes, where either precision or recall alone might present a skewed picture of model effectiveness. Choosing the F1 Score for model analysis is justified when it is essential to simultaneously account for both precision and recall, especially in tasks where a balanced performance across these metrics is critical, such as in medical diagnostics and fraud detection.

The ROC (Receiver Operating Characteristic) curve is a tool for evaluating the quality of binary classifiers. The plot depicts the relationship between the sensitivity (true positive rate) and specificity (false positive rate) of the model at different decision thresholds.

Sensitivity measures the percentage of correctly classified positive cases among all actual positive cases, and specificity measures the percentage of correctly classified negative cases among all actual negative cases. The ROC curve shows how sensitivity and specificity change as the decision threshold for classification changes.

The ROC curve is an important tool for comparing different classification models and determining their effectiveness. The closer the ROC curve is to the upper left corner of the plot (0,1), the better is the model. The Area Under the Curve (AUC) represents the area under the ROC curve, which is also used to assess model effectiveness: the higher the AUC, the better the model.

The ROC curve does not have a specific calculation formula. However, the main metrics used to construct the ROC curve are sensitivity (True Positive Rate, TPR) and specificity (1 - False Positive Rate, FPR).

To initiate the process, it is necessary to compute the classification function values for each sample in the dataset and establish the threshold cutoff value. For this calculation, a threshold value of 0.5 is used. The classification function value is the inverted priority level of the element in the group on a scale from 1 to 4, as four levels are used for ranking elements in the design. The value will be either 0 or 1, depending on whether the element was correctly added to the output data.

Sensitivity (TPR) is calculated as the ratio of correctly classified positive cases to the total number of positive cases, like recall.

Specificity, also known as 1 - FPR (False Positive Rate), is calculated as the ratio of correctly classified negative cases to the total number of negative cases:

3.5. Process improvement rating's selection

In the process of evaluating the quality of solutions aimed at addressing technical issues, the use of metrics is a necessary step to objectively assess the effectiveness of implemented changes and improvements. Gathering and analyzing relevant statistics before and after implementing artificial intelligence (AI) mechanisms becomes a key stage in calculating such metrics.

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One possible approach to evaluating the quality of solutions addressing technical issues is to compare the prevalence and severity of these problems before and after AI implementation. This could involve analyzing metrics, such as the average recovery time following system failures, to assess whether AI integration has successfully reduced the recovery duration and enhanced the overall system reliability. In addition, by analyzing the dynamics of the number of detected and corrected errors, we can assess the effectiveness of AI in detecting and resolving technical issues.

Next, after collecting relevant statistics, an analysis and calculation of metrics is conducted to assess the quality of solutions related to technical issues. One possible method for calculating such metrics involves comparing the baseline values of technical indicators before and after AI implementation.

Development time: This parameter measures the time saved in development and implementation using design tokens and assets created by artificial intelligence.

$$K_{td} = \frac{T_{dc}}{T_{dp}}, \tag{2}$$

where T_{dc} – the development time in the previous iteration; T_{dp} – the development time in the iteration after introducing AI;

Design iterations: compare the number of design iterations required to achieve desired settings with and without the use of artificial intelligence.

$$K_{Dr} = \frac{I_{Drc}}{I_{Drp}}, \tag{3}$$

where I_{Drp} represents the number of design iterations in the previous design iteration phase; I_{Drc} represents the number of design iterations after the introduction of AI;

Tracking Errors and Issues: Track the number and severity of errors or issues related to updates created by artificial intelligence

$$K_b = \frac{N_{bc} \cdot S_{bc}}{N_{bp} \cdot S_{bp}}, \tag{4}$$

where N_{bc} – number of defects in the iteration after introducing AI; S_{bc} – average severity level of defects in the previous iteration; N_{bp} – number of defects in the previous iteration; S_{bp} – average severity level of defects in the iteration after introducing AI.

Performance metrics: The product performance was measured across various configuration scenarios to ensure that the productivity was optimized by artificial intelligence.

$$P = \frac{K_{td} + K_r + K_{Dr} + K_b}{4}, \tag{5}$$

where K_{td} – coefficient of development time, K_r – coefficient of development iterations, K_{Dr} – coefficient of design iterations amount, K_b – coefficient of tracking errors and issues

Reducing the coefficients increases the value of P, indicating improved productivity. Each coefficient reflects different aspects of efficiency, and their reduction leads to a positive shift in the productivity coefficient. This approach defines a systematic method for enhancing productivity by reducing various influencing factors.

4. Case study: Application of AI based design flow for application development

Let's consider the case related to the design of sports applications (Fig. 4). This application helps users plan their gym activities, provide nutrition planning, etc. This application is designed without branding for a specific gym or fitness club; it is designed in a way that all vendors of sport activities may request rebranding of the app, and that is why this app is taken as an example of how AI may improve the rebranding process. The selection of AI for the rebranding design system represents a critical decision. Initially, the focus will be on exploring the most advanced zero-code AI platforms that enable the creation of robust and scalable solutions with a low barrier to entry.

The next section provides a detailed examination of some of the most widely recognized and influential applications currently available on a global scale (Table 1).

Google Cloud AutoML: This robust tool aligns seamlessly to transform input data into a readable and machine-processable format. The proposed model delivers high-quality results through efficient training and search models, which significantly improves workflow efficiency while minimizing errors. The intuitive interface further ensures accessibility to a diverse range of users.

Microsoft AI Builder: This toolkit provides information processing using AI models, such as prediction, form processing, object detection, classification, and object extraction.

DataRobot AI Platform: This platform allows users to build, deploy, and manage models without requiring extensive coding or data processing. This platform is designed to make it easy to build and accelerate the process of developing machine learning models.

IBM Watson Studio AutoAI: This software is designed to help data scientists and developers build and deploy machine learning models quickly and effortlessly without the need for significant manual coding or data expertise.

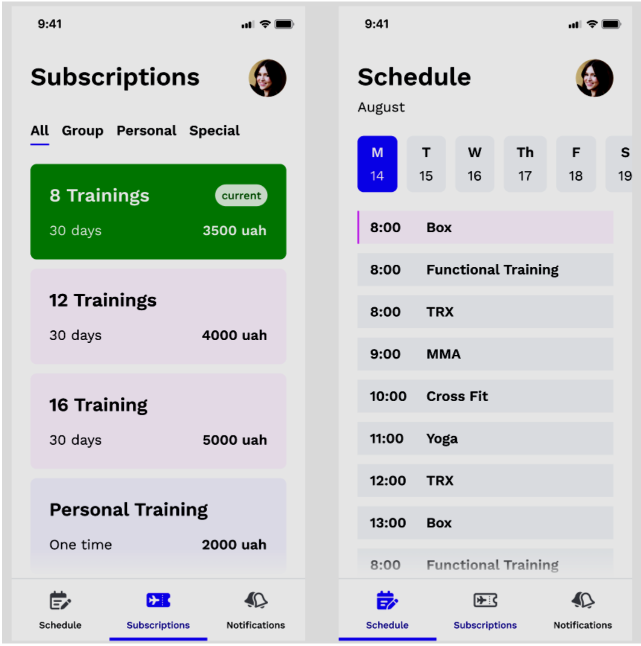

Fig. 4. Mockup of the app

Table 1

AI solutions characteristics

Solution	AI point to consider			
	Image recognition	Data preparation	Model updates	Ecosystem
Google Cloud AutoML	Yes	JSON, CSV	Evaluation, Versioning, Retraining	Storage, Database, API, Google Cloud
Microsoft AI Builder	Yes	CSV, Common Data Model, SQL Database	Evaluation, Versioning, Retraining	Power Apps, Common Data Service, Azure
DataRobot AI Platform	No	CSV, SQL Database, JSON, Text	Evaluation, Versioning, Retraining	Storage, Database, API, Cloud platforms
IBM Watson Studio	No	CSV, SQL Database, JSON, Text	Evaluation, Versioning, Retraining	Storage, Database, API, Cloud platforms

The most relevant AI solution that is suitable for the goals of the solution is Google Cloud AutoML, as it has computer vision functionality and natively works with JSON format, which is a main milestone of the use of Design Tokens.

It provides well-developed integration capabilities and efficient model computation using various methodologies and functionalities comparable to advanced systems like DataRobot AI, which primarily caters to data scientists. However, Google Cloud AI offers a lower entry barrier and is well-suited for non-professionals who require intuitive tools and user-friendly interfaces without extensive technical expertise.

Initially, the design system will be used as the primary source of truth. The proposed system serves as a foundational framework to ensure consistency and precision throughout the application. The design created using the Figma application illustrates the structural components and well-defined visual guidelines. The design system is closely integrated with the actual pages of the sports application, ensuring a seamless connection between conceptual designs and their implementation within the real-world interface. This integration guarantees that any updates or modifications to the design system are automatically propagated to the application, thereby preserving uniformity and minimizing the risk of inconsistencies.

In the second step, a brand book (Fig. 5) with descriptions of visual data about the sports vendor is taken for the rebranding process. The obtained data are used for transformation into design tokens. This information will be pushed to AI to build unified requirement model. As an output, the json data are built like the design token's json but without high-level tokens.

The Vertex pre-trained model LayoutML Document QA is used as a key component in this process. At this stage, an experienced AI engineer is engaged to provide expertise in the setup, configuration, and fine-tuning of the AI model. During this step, design tokens generated through the transformation of the design system into a unified format, along with

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semi-tokens (Fig. 6) created during the requirements transformation, undergo a second round of AI-driven transformation. This comprehensive process generates fully developed and complete design tokens, which are ready for integration into the development workflow.

Fig. 5. The brand book example

Fig 6. CSS artifacts after transformation

The third step involves the transformation of the newly generated design tokens into developer artifacts using a Style Dictionary and Design token transformation application (Fig. 7).

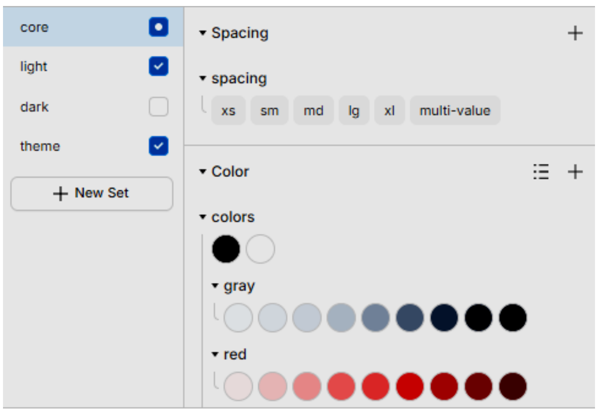

Fig. 7. Token's Studio Extension

5. Discussions

This study focuses on the development of AI-based UI design system to improve a company white labeling (aka rebranding) process. This is the process of removing a product or service's original branding and replacing it with the branding of another company or individual. The use of this approach has also shown a significant boost in performance during designer-to-client communication and designer-to-developer communication [17] (Table 2).

Table 2

Metrics-based design systems comparison

	Existing design system	AI-based design system
Development Time	Approximately 40h	May be reduce to 24h
Design Iterations	3-5 rounds	1-2 rounds
Customization Requests	5-20 requests	2-4 requests

In contrast, design transformation is automatic, and the process of rebranding does not require manual actions; the process of requirement clarification [18] and verification is faster up to 25%. As a point of interest, the number of denial calls was reduced by half, and the customer satisfaction coefficient demonstrated improvement in communication and understanding between the client and performer: Precision, 0.77; Recall, 0.63; F1 Score, 0.65.

The F1 score of 0.65 can be considered fairly good; however, determining whether it is "good" or "insufficient" can depend on the specific context and tasks the model is addressing (Table 3).

Table 3

Model outcome results

The input data contains	The formed data contains	The number of design elements
+	+	17
-	+	5
+	-	3
-	-	0

An F1 score of 0.65 indicates that the model achieved an acceptable balance between precision and recall in classification. However, it's important to note that in other cases, higher or lower F1 scores may be considered more or less satisfactory depending on the specific use of the model.

For instance, in the context of an individual design system where accuracy and recall are important, such as accurately determining individual user preferences, an F1 score of 0.65 can be considered high. However, in medical diagnostics where high accuracy is crucial, this value may require further improvement of the model.

When calculating the ROC AUC Receiver Operating Characteristic Area Under the Curve) (Fig. 8)

For the output data of the test set, the results indicate that 17 elements were correctly classified, while 5 elements were incorrectly classified within the first class. These outcomes serve as the foundational data for calculating the ROC AUC metric, which is used to evaluate the performance of a classification model across a range of decision thresholds.

This analytical methodology helps us make informed decisions regarding further steps toward improving these processes (Table 4).

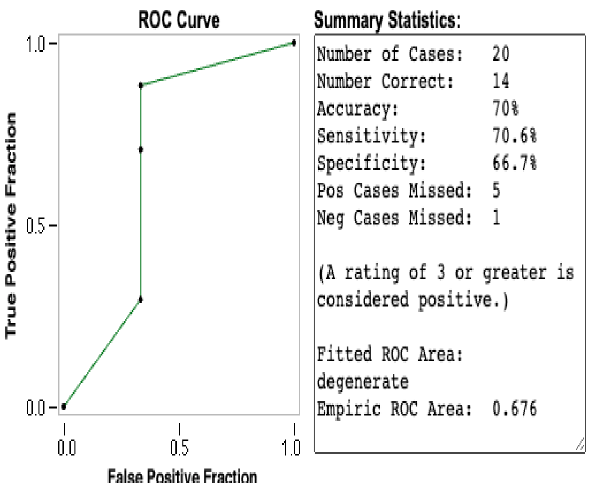

Fig. 8. ROC AUC of the first type

Table 4

Improvement coefficient comparison

Characteristics	Existing process	Improvement coefficient
Development time	± 40h	0.6
Code quality	± 5h	0.5
Design iterations	3-5 rounds	0.2
Tracking errors and issues	15 defects Severity 3	0.8
Productivity	1	0.52

The analysis yielded an AUC metric of 0.676, with evaluations for other classes demonstrating comparable scores, indicating satisfactory performance. The primary objective is to identify and quantify improvements in the development and implementation of design processes through clearly defined objective criteria. This approach enables the refinement and optimization of methodologies and strategies to maximize productivity and quality. To achieve this, relevant indicators and their changes over time are systematically analyzed, using coefficients as measurement tools. This methodology provides a structured framework for objectively assessing the effectiveness of implemented changes and evaluating their overall impact on development and design processes.

6. Conclusions

In conclusion, the integration of AI into the process of UI design system adaptation for end customer requirements represents a significant advancement in the field of user experience (UX) design. This innovative approach combines the capabilities of AI, such as machine learning and data analysis, with the principles of user-centered design to create interfaces that are more personalized, intuitive, and responsive to individual user needs. Through the use of AI algorithms, UI design systems can dynamically adapt to user preferences, behavior patterns, and contextual factors, ultimately leading to enhanced user satisfaction and engagement.

The AI-based process has demonstrated a reduction in the time required for the development process and a decrease in the number of iterations required for design and code reviews. The reduced time and iterations have contributed to increased efficiency and productivity in the overall development workflow.

Based on the analysis results, it is evident that the implementation of artificial intelligence has significantly changed the process, thereby improving its efficiency. This is substantiated by numerical indicators and metrics demonstrating positive changes in relevant process parameters, including a reduction in the time required to complete tasks, an improvement in result accuracy, and a decrease in errors. These changes indicate the successful integration of artificial intelligence into the process and its positive impact on performance.

Further research in the domain of AI-driven UI design system adaptation should encompass ethical dimensions, including privacy, algorithm transparency, and bias reduction, as well as foster stronger collaboration between human designers and AI suggestions to preserve creativity. Investigating the enduring effects of AI-adapted UIs on user behavior, extending adaptations seamlessly across platforms, and enabling real-time adjustments for personalized experiences are crucial. Empowering users with control over AI-generated suggestions and tailoring UIs to diverse cultural and contextual factors should also be prioritized to create adaptable, user-centric interfaces while maintaining ethical standards.

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Contribution of authors

Kyrylo Polishchuk was responsible for developing the main idea of the research and creating the proof of concept. He was also responsible for researching existing and developing new appropriate metrics for measuring the success of AI-based process implementation.

Eugene Brezhniev was tasked with curating and moderating the research and guiding the development of new metrics to measure the success of process updates. He also provided initial guidance regarding the idea and research implementation.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research, and its results presented in this paper.

Financing

The research was conducted without financial support.

Data availability

The manuscript contains no associated data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods in their work.

All authors have read and agreed to the publication of the final version of this manuscript.

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ВИКОРИСТАННЯ ШТУЧНОГО ІНТЕЛЕКТУ В ПРОЦЕСІ АДАПТАЦІЇ СИСТЕМИ ДИЗАЙНУ ІНТЕРФЕЙСУ КОРИСТУВАЧА ДО ВИМОГ КІНЦЕВОГО КЛІЄНТА

К. В. Поліщук, Є. В. Брежнєв

Ця робота присвячена демонстрації підходу до розробки системи дизайну інтерфейсу користувача на основі штучного інтелекту для покращення процесу ребрендингу компанії. Це процес видалення оригінального бренду продукту чи послуги та заміна його брендом іншої компанії або особи. Основні цілі дослідження включають розробку методів оптимізації ребрендингу, автоматизацію доставки результатів роботи дизайнерів та досягнення покращення процесу адаптації дизайну для кінцевого дистриб'ютора, відомого як процес білого маркування. Об'єктом дослідження є існуючий процес ребрендингу та аналіз готових рішень з використанням штучного інтелекту для його покращення. Метою дослідження є виявлення інноваційних методів впровадження штучного інтелекту в процес ребрендингу для полегшення та прискорення завдань, пов'язаних з дизайном та маркетингом. Методи дослідження включають аналіз існуючих практик ребрендингу, розгляд готових рішень з використанням штучного інтелекту, а також експерименти та практичне застосування нових методів для покращення процесу. Наукова новизна дослідження полягає у впровадженні штучного інтелекту в галузь ребрендингу та розробці ефективних методів для його покращення. У результаті покращення досягаються завдяки розгортанню рішення на основі штучного інтелекту, ретельно розробленого навколо концепції дизайнерських токенів, які служать ключовим елементом для стандартизації та гармонізації роботи дизайнерів. Ця методологія передбачає всебічне налаштування моделі ШІ для безперебійної інтеграції з існуючими системами дизайну, тим самим полегшуючи трансформацію систем дизайну та бренд буків у реальні дизайнерські токени. Процес інтеграції ШІ у робочі процеси дизайну включає широке навчання моделей з використанням відкритих даних спільноти. Особливу увагу приділено вибору наборів даних, забезпечуючи, щоб вони відповідали суворим критеріям оцінки якості та ефективності навчання штучного інтелекту. Ці критерії охоплюють такі фактори, як релевантність даних, різноманітність і репрезентативність, а також міркування щодо етичної та правової відповідності. На завершення: використовуючи цей ретельно розроблений підхід, організації можуть ефективно використовувати потужність ШІ для впровадження трансформаційних змін у процеси дизайну, зрештою підвищуючи ефективність, послідовність та інноваційність у своїй діяльності. Приймаючи різні аспекти інтеграції ШІ, ця робота надає оновлений процес дизайну інтерфейсу користувача з можливістю використання ШІ під час розробки орієнтованого на клієнта дизайну.

Ключові слова: дизайн-токени; штучний інтелект; адаптація дизайну; проектування системи; біле маркування; адаптація на основі ШІ; автоматизація дизайну.

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