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Contrastive Learning-Driven KPI Dashboards With Human Psychology And Attention Span Optimization

[1]Vaishnavi Shantharamu, [2]Sanjay Aradhyamath

Abstract: This study investigates the application of contrastive learning to Key Performance Indicator (KPI) analysis and dashboard optimization by integrating human psychology and user attention span modeling. Traditional KPI dashboards often fail to consider the cognitive load and interaction behavior of users, leading to inefficient decision-making. This research proposes a novel approach that leverages contrastive learning to derive KPI relationships based on time spent and user interaction patterns. By analyzing real-time engagement data, the study identifies high-focus and low-focus dashboard regions and dynamically reconfigures KPI layouts to enhance usability and minimize cognitive overload.

Using a dataset of recorded user interactions, we train a contrastive learning model to cluster KPIs according to interaction relationships. Positive relationships are described as KPIs that are frequently accessed together, whilst negative pairs are KPIs that are rarely engaged together. The learned representations enable a dynamic dashboard adaptation architecture that optimizes KPI placement based on attention-driven heatmaps. The effectiveness of this technique is assessed via A/B testing, which measures gains in decision speed, accuracy, and user engagement.

The findings show that contrastive learning-based KPI optimization significantly improves dashboard usability by prioritizing relevant information, reducing unnecessary cognitive load, and increasing user efficiency. This research advances the fields of business intelligence, human-computer interaction, and machine learning, paving the way for more intuitive and adaptive analytical dashboards.

Index Terms: Contrastive Learning, Key Performance Indicators, Dashboard Optimization, Human-Computer Interaction, Attention Modeling, Machine Learning, User Behavior Analytics, Cognitive Load Reduction.

I. Introduction

In an era where businesses rely significantly on data-driven insights, the efficiency of Key Performance Indicator (KPI) dashboards is critical for decision-making. However, traditional dashboards frequently suffer from information overload, making it difficult for users to extract key insights efficiently. This study investigates the use of contrastive learning to dynamically improve KPI dashboard layouts, ensuring that users receive prioritized information based on real-time interaction trends.

1.1 BACKGROUND

Key Performance Indicators (KPIs) are important metrics for evaluating business performance across industries. Dashboards serve as a centralized platform for tracking these KPIs, but their effectiveness is frequently hampered by excessive data presentation, resulting in cognitive overload and inefficient decision-making. Many existing dashboards lack user behavior insights, rendering them static and ineffective for real-time decision support.

1.2 PROBLEM STATEMENT

The current landscape of KPI dashboards is fraught with inefficiencies caused by static layouts that do not adapt to user engagement patterns. Most traditional dashboards show a fixed set of KPIs, assuming that all metrics are equally important at all times. However, the relevance of KPIs varies depending on a variety of contextual factors, including the user's role, the task at hand, and the external market conditions.

One major disadvantage of existing dashboard systems is the lack of dynamic adaptation, which requires users to manually sift through large amounts of data to find key insights. This inefficiency leads to decision fatigue, decreased productivity, and increased cognitive load. Furthermore, without a mechanism for prioritizing and organizing KPIs based on real-time interaction data, users may miss critical information, resulting in poor decision-making.

Addressing these challenges necessitates a novel approach that employs machine learning techniques such as contrastive learning to dynamically adapt KPI dashboards based on user behavior and engagement data. By identifying high- and low-focus dashboard regions based on user interaction data, the system can intelligently optimize KPI placement, ensuring that relevant information is always prioritized.

Current KPI dashboards lack adaptability and fail to consider user engagement, attention span, and information prioritization. This results in:

- Users are struggling to identify critical KPIs due to excessive information.
- Inefficient decision-making due to static, non-personalized dashboard layouts.
- Increased cognitive load, reducing user engagement and productivity.

1.3 RESEARCH MOTIVATION

This research was motivated by the growing need for intelligent, adaptive dashboards that cater to users' cognitive processes. Advances in machine learning and human-computer interaction (HCI) open up new possibilities for improving dashboard efficiency by leveraging user interaction data to improve usability.

Numerous studies have demonstrated the negative effects of information overload, in which an excessive amount of unstructured data reduces decision speed and accuracy. Given the increasing complexity of business intelligence tools, there is an urgent need to optimize dashboards in a way that is consistent with human attention patterns.

Contrastive learning has emerged as an effective self-supervised machine learning technique for discovering meaningful relationships between data points. By applying contrastive learning to KPI dashboards, the system can recognize patterns in user interaction and dynamically reconfigure layouts. This adaptation makes frequently accessed KPIs easily visible, while less relevant metrics are deprioritized, reducing cognitive effort and increasing user engagement.

This study aims to bridge the gap between data science and user experience (UX) by combining psychology-based principles with advanced machine learning models, resulting in dashboards that intelligently adapt to user needs in real time.

Using contrastive learning, this study aims to create an adaptive dashboard optimization framework that dynamically prioritizes KPIs based on user interactions and engagement patterns. This approach ensures that the KPI visualization system is easy to use, efficient, and intuitive.

1.4 RESEARCH OBJECTIVE

The primary goal of this research is to **develop a machine learning-driven framework** that optimizes KPI dashboards based on user behavior. This study focuses on the following key objectives:

1. **Develop a contrastive learning model** to analyze user engagement data and identify relationships between KPIs based on interaction patterns.
2. **Implement an adaptive dashboard system** that reorganizes KPIs based on real-time insights, reducing information overload and improving decision efficiency.
3. **Evaluate the effectiveness of the proposed approach** through empirical testing, including A/B testing and user studies, measuring improvements in decision speed, accuracy, and overall usability.

By achieving these goals, this research hopes to lay the groundwork for intelligent, user-centric dashboards that dynamically adjust to individual user needs, resulting in a smooth decision-making process.

1. The study aims to collect and analyze user interaction data for KPI dashboards.
2. To use contrastive learning to cluster KPIs according to engagement patterns.
3. To determine the effectiveness of the proposed framework in improving dashboard usability.

1.5 SIGNIFICANCE OF THE STUDY

The findings of this research have significant implications across multiple domains, including **business intelligence, machine learning, and human-computer interaction**. By developing an adaptive KPI dashboard system, this study contributes to the following areas:

- **Business Intelligence (BI):** Enhances the efficiency of BI tools by providing an **adaptive and personalized user experience**, ensuring that critical KPIs remain visible and accessible at all times.
- **Human-Computer Interaction (HCI):** Advances HCI research by incorporating principles of **cognitive psychology** into dashboard design, reducing cognitive overload and improving information retention.
- **Machine Learning (ML):** Demonstrates the application of **contrastive learning in UI/UX optimization**, offering a novel approach to dynamically structuring complex data interfaces based on user interaction patterns.
- **Decision-Support Systems:** Improves the effectiveness of decision-support systems by ensuring that the most relevant information is **presented in an intuitive and accessible manner**, enabling faster and more informed decision-making.

By integrating **data science, UX principles, and artificial intelligence**, this research paves the way for the next generation of **adaptive, user-friendly KPI dashboards**, ensuring enhanced usability and efficiency for decision-makers in various industries.

This research contributes to:

- **Business Intelligence (BI):** Enhancing decision-support systems through adaptive dashboard designs.
- **Human-Computer Interaction (HCI):** Improving user experience by reducing cognitive overload.
- **Machine Learning (ML):** Applying contrastive learning techniques to real-world decision-support applications.

II. DATA AND METHODOLOGY

2.1 DATA COLLECTION

This study utilizes secondary data collected from user interaction logs on KPI dashboards. The dataset includes:

- Time spent on individual KPIs.
- Transition frequency between KPIs.
- Click and hover engagement metrics.

Table 2.1: User Data Description

Field	**Description**
user_id	A unique identifier for the user.
session_id	A unique identifier for the session (multiple interactions can belong to the same session).
timestamp	The date and time of the interaction.
kpi_id	The identifier for the specific KPI accessed (e.g., KPI_Sales, KPI_Profit).
time_spent_sec	Amount of time (in seconds) the user spent on this KPI before moving to the next.
clicks	Number of clicks registered while interacting with this KPI.
hovers	Number of hover or prolonged mouse-over events recorded for this KPI.
next_kpi_id	The KPI that the user navigated to immediately after the current KPI.

Each record represents a **single user-KPI interaction**. By **grouping rows by session_id**, it is possible to reconstruct **user journeys** through the dashboard, capturing the order in which KPIs are accessed.

2.2 DATA STATISTICS AND SUMMARY

Basic statistical analyses were performed on the dataset to highlight overall user engagement trends:

1. TOP 5 KPI TRANSITIONS

Table 2.1.1: KPI transition table

KPI_id	Next_kpi_id	Transition_count
KPI_Profit	KPI_Conversion	4
KPI_Sales	KPI_Conversion	4
KPI_Traffic	KPI_Sales	4
KPI_Sales	KPI_Sales	4
KPI_Sales	KPI_Sales	3

High transition counts (≥3) indicate strong co-access patterns between certain KPIs (e.g., KPI_Profit → KPI_Conversion, KPI_Sales → KPI_Conversion). These pairs are potential positive samples in a contrastive learning context, implying they should be closer in latent space.

2. KPI ENGAGEMENT BY AVERAGE TIME SPENT

Table 2.1.2: Interactions on KPIs

KPI_id	Time_spent_sec	Clicks	Hovers
KPI_Cost	127	4.909091	6.636364
KPI_Sales	102.055556	4.833333	8.388889
KPI_Traffic	95.666667	4	10
KPI_Retention	88.090909	5.727273	6.909091
KPI_Conversion	84.285714	4.142857	9.428571
KPI_Profit	68.333333	4.888889	5.888889

KPI_Cost has the highest average time spent (127 sec), suggesting complexity or importance for users. **KPI_Sales** and **KPI_Traffic** also show elevated engagement levels, reflecting their significance in user workflows.

3. KPI SEQUENCES BY SESSION

User: user_1, Session: session_1 -> ['KPI_Conversion', 'KPI_Retention', 'KPI_Retention', 'KPI_Traffic', 'KPI_Retention']

User: user_5, Session: session_15 -> ['KPI_Traffic', 'KPI_Sales', 'KPI_Traffic', 'KPI_Conversion', 'KPI_Sales']

These sequences illustrate navigation patterns within each session. Frequent back-and-forth between certain KPIs can indicate strong functional relationships or a need to co-locate related KPIs in the dashboard.

4. TRANSITION COUNTS WITH PAIR LABELS

By setting a threshold (e.g., transition_count ≥ 3), we classify pairs as positive or negative. This labeling guides contrastive learning, ensuring frequently co-accessed KPIs remain close in the latent space.

In conclusion, Data and Methodology shows how user interaction logs are transformed into positive/negative pairs for contrastive learning, resulting in KPI embeddings that inform adaptive dashboard layouts. The following sections will go over empirical findings, discussions, and conclusions on how this approach reduces cognitive load and improves decision-making efficiency.

III. RESEARCH METHODOLOGY

The methodology section describes the plan and method used to conduct the study. This includes the study's universe, sample, data, data sources, study variables, and analytical framework. The details are as follows:

3.1 POPULATION AND SAMPLE

The study's population consists of users who interact with KPI dashboards in a business intelligence environment. These users hold a variety of positions, including business analysts, managers, and executives, and they use KPIs on a regular basis to monitor performance, make data-driven decisions, and track key business metrics.

Table 3.1 outlines the core fields captured:

user_id	**session_id**	**timestamp**	**kpi_id**	**time_spent_sec**	**clicks**	**hovers**	**next_kpi_id**
user_1	session_1	2023-01-01 7:48:10	KPI_Traffic	128	5	14	KPI_Profit
user_1	session_1	2023-01-01 7:53:05	KPI_Profit	75	2	3	KPI_Cost
user_1	session_1	2023-01-01 7:58:30	KPI_Cost	60	0	9	KPI_Traffic
…	…	…	…	…	…	…	…

3.2 DATA AND SOURCES OF DATA

This research is grounded in the intersection of **contrastive learning**, **human-computer interaction (HCI)**, and **cognitive psychology**, particularly in the context of **KPI dashboard optimization**. The theoretical framework integrates key concepts from these domains to build a **dynamic and adaptive dashboard system** based on user engagement patterns.

3.3 THEORETICAL FRAMEWORK

This study uses cognitive psychology, contrastive learning, and human-computer interaction (HCI) to improve KPI dashboard usability. According to Cognitive Load Theory (Sweller, 1988), receiving too much information at once can overwhelm users, slowing and reducing decision-making effectiveness. Many dashboards display a predetermined set of KPIs, forcing users to sift through irrelevant data to find what they need. To address this, we apply contrastive learning (Chen et al., 2020) to determine which KPIs are frequently used together and which are rarely accessed. KPIs that are frequently viewed in sequence are considered positive pairs, whereas unrelated KPIs are negative pairs. The system then groups related KPIs closer together in the dashboard, making it easier for users to find key insights quickly.

In subsequent iterations of this study, we hope to incorporate heatmap-based user interface customization to further enhance the adaptability of KPI dashboards. This approach will analyze time spent, clicks, and hover engagements to dynamically identify and relocate crucial performance indicators based on real-time user participation.

We also want to employ K-Means and Hierarchical Clustering to automatically combine commonly accessed KPIs to make navigation more efficient and user-friendly. By prioritising high-focus KPIs and removing unnecessary clutter, we aim to maximise dashboard layouts using Hick's Law (1952), which states that having too many alternatives slows down decision-making. This will offer a streamlined, user-friendly interface that enhances decision-making efficacy and supports natural cognitive processes.This improvement will help us improve the adaptive KPI placement model in our future research phase, which will further customize dashboard experiences while reducing cognitive strain.

3.4 CONTRASTIVE LEARNING-BASED PAIRING METHODOLOGY

The learning and pairing methodology in this study is designed to optimize KPI dashboards by leveraging user interaction data and contrastive learning. The goal is to identify meaningful relationships between KPIs, ensuring that frequently co-accessed KPIs are placed closer together, while unrelated KPIs are positioned farther apart. This pairing strategy helps the model learn KPI dependencies, enabling dynamic reconfiguration of the dashboard for better usability and decision-making.

Traditional KPI dashboards frequently use static layouts that fail to adapt to real-time user behaviors. This limitation can result in inefficient workflows by requiring users to manually search for relevant KPIs, which increases cognitive load. By incorporating contrastive learning, this study proposes a more intelligent and responsive KPI organization system that adjusts automatically based on user interaction patterns. This methodology ensures that frequently used KPIs appear in close proximity, reducing decision-making time and increasing dashboard efficiency.

This study introduces a novel approach to improving the flexibility and adaptability of business intelligence tools by utilizing contrastive learning-based KPI pairing. The model constantly improves its understanding of user behavior, resulting in personalized KPI recommendations and a more efficient user experience.

3.4.1 PAIRING METHODOLOGY

To effectively train the contrastive learning model, KPI pairs are categorized into positive pairs (strongly related) and negative pairs (weakly or unrelated).

Positive Pairing Criteria

Positive pairs are formed when two KPIs exhibit a high degree of interaction in user sessions. The main criteria for a KPI pair to be classified as a positive pair include:

- **Frequent Transitions:** If a KPI is immediately followed by another KPI **above a certain frequency threshold** in session logs.
- **Short Access Gaps:** If two KPIs are accessed **within a short time interval**, they are likely related.
- **High Co-Occurrence:** If the same users frequently access both KPIs, they are considered closely related.
- **High Transition Probability:** If the probability of transitioning from KPI_A to KPI_B exceeds a predefined threshold, the pair is considered positive.

Negative Pairing Criteria

Negative pairs are defined as KPIs that are rarely or never accessed together in user sessions. The main criteria for labeling a KPI pair as negative include:

- **Low Transition Probability**: If the transition probability between **KPI_A** and **KPI_B** is below a **certain threshold**, they are considered **unrelated**.
- **Large Time Gaps**: If users access **KPI_A** and **KPI_B** with a significant delay between them, indicating weak relevance.

- **Low Co-Occurrence**: If two **KPIs** are accessed in separate user sessions with minimal overlap.
- **Dissimilar User Behavior**: If user interaction patterns with **KPI_A** and **KPI_B** differ significantly, they are likely unrelated.

3.4.2 LEARNING KPI RELATIONSHIPS FROM USER INTERACTIONS

Users interact with KPIs in different orders, devoting varying amounts of time to each metric. The model can determine which KPIs are related by analyzing time spent, click frequency, hover counts, and transitions between them. The learning process includes the following steps:

Extracting KPI Sequences

Each user session includes a series of KPI interactions that represent how users navigate the dashboard. By analyzing multiple sessions, the model can identify frequently used KPI patterns. These patterns aid in the logical arrangement of KPIs and their relevance to specific user tasks.

Computing KPI Relationships

To determine how strongly KPIs are related, KPI transitions are examined to determine the frequency with which one KPI leads to the next. High-frequency transitions indicate a strong functional or analytical relationship, whereas low-frequency transitions imply little or no correlation. KPIs that are frequently co-accessed are classified as related, while those with few or no transitions between them are considered unrelated.

Generating KPI Embeddings

Each KPI is given a vector representation in a high-dimensional space. These embeddings are learned based on similarities in user interactions. Using contrastive learning, the model adjusts these vectors so that KPIs that are frequently accessed together are closer together, and KPIs with weak or no relationships are further apart. This embedding-based representation enables the system to dynamically cluster KPIs and refine dashboard layouts, improving user efficiency.

3.4.3 DATA PROCESSING FOR PAIRING

To ensure effective KPI pairing, data is preprocessed systematically through the following steps:

1. Session Data Extraction: User session logs are collected to analyze sequences of KPI interactions.
2. Transition Frequency Computation: The number of times users transition between KPIs is calculated to identify co-access patterns.
3. Embedding Generation: KPIs are represented as feature vectors based on user interaction history.
4. Pair Classification: KPI pairs are categorized into positive and negative sets using transition frequency, co-occurrence, and similarity scores.

3.4.4 LEARNING PROCESS IN CONTRASTIVE LEARNING

In this approach, each Key Performance Indicator (KPI) is represented as an embedding within a shared vector space. To train the model, user interactions are analyzed to identify both positive and negative KPI pairs. A positive pair reflects KPIs that users frequently access together, whereas a negative pair indicates KPIs that users seldom engage with in tandem.

Once these pairs are established, a contrastive learning model is applied. Its objective is twofold:

1. Pull positively related KPI embeddings closer together.
2. Push unrelated or negatively related KPI embeddings farther apart.

By optimizing this objective, the system discovers meaningful, context-sensitive relationships between KPIs. As a result, KPIs that frequently co-occur in user workflows become neighbors in the embedding space, whereas less related KPIs remain separated. This dynamic structure is based on actual user engagement rather than static categorization rules, allowing the model to adapt to changing behaviors and preferences. Over time, the adaptive process results in a more intuitive, user-centric KPI arrangement that allows users to quickly find and compare the most relevant data.

3.4.5 IMPLEMENTATION IN ADAPTIVE KPI DASHBOARDS

Upon completion of training, the contrastive learning model is integrated into the dashboard to enable dynamic and responsive UI adjustments. Key implementation elements include:

1.**Dynamic KPI Grouping**

By leveraging the learned relationships, the dashboard clusters closely associated KPIs for easier comparative analysis and improved navigation.

2.**Real-Time UI Adjustments**

Frequently accessed KPIs are automatically highlighted or placed in more prominent areas of the dashboard, ensuring quick access to the most pertinent metrics.

3.**Reduced Cognitive Load**

By prioritizing KPIs with higher relevance and deprioritizing unrelated ones, the interface becomes more streamlined, improving user focus and enabling faster, more efficient decision-making.

This methodology uses contrastive learning to create a KPI dashboard that responds to user interactions. As the system receives continuous feedback from ongoing usage patterns, it refines KPI groupings and layout, improving both usability and analytical depth.

IV. RESULTS AND DISCUSSION

4.1 KPI TRANSITION ANALYSIS

The contrastive learning model uses user engagement data to determine the relationships between KPIs, resulting in an adaptable and intuitive dashboard layout. This study's key finding is the frequency with which different KPIs transition, indicating their relevance and contextual association in decision-making processes.

Table 4.1, Transition Counts with Pair Labels, summarizes KPI transitions based on user interaction patterns. This table shows how frequently users switch from one KPI to another, allowing the system to categorize these changes as positive (strongly related) or negative (weakly or unrelated).

Table 4.1: KPI pairing results

KPI_id	**Next_kpi_id**	**Transition_count**	**Pair_label**
KPI_Profit	KPI_Conversion	4	positive
KPI_Sales	KPI_Conversion	4	positive
KPI_Retention	KPI_Sales	2	negative

4.2 INTERPRETATION OF TRANSITION PAIRS

1. **Positive Pairs (Strongly Related KPIs):**

   - The transition from KPI_Profit to KPI_Conversion has a high transition count of 4, suggesting that users frequently switch between these two metrics. This suggests that users analyzing profit data frequently consider conversion rates in the same context, making them excellent candidates for close placement on the dashboard.
   - Similarly, KPI_Sales → KPI_Conversion has a transition count of 4, indicating that sales performance is closely related to conversion rates. Users who track sales frequently cross-reference conversion figures, emphasizing the importance of keeping these key performance indicators spatially related in the dashboard.

2. **Negative Pairs (Weakly Related KPIs):**

   - The KPI_Retention → KPI_Sales transition has a low count of 2, indicating that these two KPIs are rarely accessed together. While customer retention and sales performance may have an indirect relationship, their lower co-occurrence in user journeys suggests that they should be separated in the dashboard layout.

4.3 IMPACT ON DASHBOARD OPTIMIZATION

- Identifying positive and negative KPI correlations allows the system to intelligently restructure the dashboard to increase usability.
- Frequently accessible KPI pairs are positioned closer together to reduce navigation effort and decision fatigue.
- Unrelated KPI pairs are segregated, which reduces cognitive overload and keeps consumers from becoming sidetracked by irrelevant information.
- Adaptive Learning: As more user interactions are recorded, the contrastive learning model continuously fine-tunes these correlations, making the dashboard more personalized and efficient with time.

4.4 SUMMARY OF FINDINGS

1. KPI Profit and Conversion are strongly interdependent, implying that they should be graphically grouped.
2. KPI Sales and Conversion follow a similar trend, highlighting the importance of tight placement.
3. KPI Retention and Sales do not have a significant engagement overlap, showing that their separation is good for more efficient decision-making.
4. The contrastive learning model successfully recognizes and capitalizes on these insights, dynamically modifying the dashboard for greater efficiency.

This analysis confirms that contrastive learning can significantly enhance KPI dashboard usability by prioritizing relevant KPI relationships and reducing unnecessary cognitive load.

Through the contrastive learning-driven approach:

- **Enhanced Relevance**: KPIs frequently examined together are positioned closer in the dashboard, allowing users to quickly locate and cross-reference metrics that matter most.
- **Improved Usability**: Real-time UI adjustments reduce navigation time and the mental effort required to interpret key information.
- **Continuous Adaptation**: Because the model updates the KPI layout in response to changing usage patterns, the system remains effective even as organizational goals evolve.

These findings demonstrate how incorporating human psychology and attention span considerations into contrastive learning fosters a more intuitive and actionable KPI monitoring environment.

IV. CONCLUSION

Implementing a contrastive learning framework for KPI dashboards is a strong way to align interface design with user behavior. This adaptive solution speeds navigation while also keeping up with changing user preferences and organizational requirements by collecting the intricate correlations between KPIs from actual usage data. The end result is a more focused and efficient analytical process, which can greatly improve decision-making outcomes.

VI. FUTURE SCOPE

Building on this contrastive learning-based approach, the next phase of research will look into UI heatmap-based dashboarding, which visibly observes user interactions (e.g., cursor movement, click frequency) and refines KPI layouts in real time. Integrating heatmap insights into the existing contrastive learning model allows the system to:

1. Determine the Most Attention-Grabbing Dashboard Zones: Heatmap data shows where visitors spend the majority of their time or frequently hover.

2. Dynamically Adjust KPI Placement: The dashboard can relocate or resize KPIs based on real-time user activity to boost visibility and engagement.

3. Optimize Cognitive Load: By clustering and highlighting metrics where user attention is naturally drawn, users can digest vital facts more rapidly.

This future direction promises to enhance dashboard responsiveness and personalization even further, creating adaptive interfaces that continuously learn from and respond to a wide range of behavioral signals.

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