WeB-Bit

Designing with AI : Video to Mindmaps

Source: OpenAI's ChatGPT

w e - b - b i t

Make webs from bits

"Exploring the Potential of Generating AI-Mindmaps from Videos to Enhance Video Analysis Workflows for Designers"

Author
Karthi Saravanan
Student number : 5716187

Chair
Dr. Evangelos Niforatos
Assitant Professor | Sustainable Design Engineering Department of IDE, TU Delft

Mentor
Tianhao He
PhD candidate | Industrial Design Engineering, TU Delft

TU Delft Delft University of Technology

Faculty of Industrial Design Engineering

A thesis report presented for the degree of Master of Science in Integrated Product Design.

Acknowledgement

Firstly, I would like to thank my chair, Evangelos Niforatos, for guiding me through this journey. It has been incredibly easy to work with him, and I truly appreciate his honest feedback and the valuable discussions we had. His humor and straightforward answers made collaboration effortless and enjoyable, qualities I hope to learn from him. Both Tianhao and Evan provided high-level insights that helped me make the most important decisions necessary for this project. Over time, I realized their well-thought-out advice helped me avoid many potential mistakes. After sharing experiences with my friends in IDE, I can confidently say I had the most responsive and easy-to-work-with chair and mentor. Weekly meetings and prompt email replies within a day were invaluable, helping me stay on track and receive quick feedback without falling behind.

Secondly, I want to thank my family, who have been the foundation of my journey. Amma and Appa, this degree is yours as much as it is mine. Whether it was monetary or emotional support, my Amma has always been the cornerstone of my life, holding our family together, her career, and motivating me through difficult days. Thank you both for giving me the chance to chase the dreams you couldn’t.

Last but not least, I want to thank my friends, my family in this foreign land. They have been my study buddies and brainstorming partners, providing me with shelter, food, and smokes when the grind got heavy. Laura, Ramya, Varun, Anshu, and Chinmayi, your love and support were the verses that kept me going.

Abstract

In today's world, products are increasingly intertwined with our daily lives, becoming more intricate. To design these interactions effectively, designers need to comprehend both the people involved in the activities and the technical systems. As user-centered design spreads, the focus shifts from viewing design as problem-solving to recognizing it as the social creation of new possibilities. This shift highlights the importance of users and their everyday lives, as well as their interactions with the product in designing.

Videos serve as a powerful tool for learning about users, their behaviors, and interactions. Video Based Design (VBD) involves analyzing videos to interpret, infer, question actions, and understand the user's thought process. However, this approach can extend the time and analytical rigor needed due to the extensive analysis required to draw valid conclusions from the video content. To streamline this process and enhance researchers' workflow, we prototyped a tool that can produce mind maps from videos. These mind maps serve as a visual representation of the video's key concepts in an organized manner. This tool utilizes Large Language Models (LLMs) to process multimodal video inputs and output the generated mind maps.

To assess the impact of mind maps on the video-based design process, an experimental study was conducted involving 28 designers. Participants were asked to watch two videos from different contexts and then engage in activities using mind maps generated by both the LLM and a human designer. Through quantitative and qualitative analysis of the study data, we gained valuable insights, identified strengths and weaknesses, and proposed design enhancements for the next version of the tool.

Keywords

Large language models, Human computer interaction, video analysis, video-based design, mind map, research for design

Index

Acknowledgement
Abstract
Keywords

Chapter 1 Introduction **11-16**
1.1 Background
1.2 Research Methodology
1.3 Research Outline

Chapter 2 Literature Review **17-32**
2.1 Video-Based Design
- 2.1.1 Importance of User-centered design
- 2.1.2 The Role of Video-Based Design in User-Centred Design
- 2.1.3 The Value of Video and Non-Verbal Cues in Design
- 2.1.4 The Role of Video in Design
- 2.1.5 Applications of Video Based Design
- 2.1.6 Unveiling Insights : A Video Analysis Journey
- 2.1.7 Hurdles in VBD

2.2 Mitigating Hurdles in VBD: Exploring AI Generated Mind Maps
- 2.2.1 Introduction to Mind Maps
- 2.2.2 Using Mind Maps to Capture Video Content
- 2.2.3 Effectiveness of Large Language Models in generating Mindmaps
- 2.2.4 Effectiveness of Mind Maps in Enhancing Learning and Memory Retention
- 2.2.5 Using Mindmaps to Capture Video Content
- 2.2.6 Method To Evaluate The Generated Mind maps : Holistic Scoring

2.3 Designing Human-AI Co-Creative Systems
- 2.3.1 Determinants Influencing the Effectiveness of Human-AI Co-Creation Systems
- 2.3.2 Potential Pitfalls in Integrating AI Systems in Human Centered Design

Chapter 3 System Design **33-38**
3.1 Data Input and Processing: Extracting Meaningful Information
3.2 Prompting
- 3.2.1 Converting Frame-wise Descriptions To Paragraph Description
- 3.2.2 Generating JSON File

3.3 User Interface
- 3.3.1 Layout

Chapter 4 Study **39-52**
4.1 Problem Statement
- 4.1.1 User Experience Map
- 4.1.2 Addressing Pain Points with AI-Generated Mind Maps

4.2 Study Design
- 4.2.1 Research Study Objectives
- 4.2.2 Research Questions
- 4.2.3 Chosen Contexts for the Study
- 4.2.4 Baseline Condition for Human-Generated Mind Maps
- 4.2.5 Apparatus

4.2.6 Participants
4.3 Evaluation Parameters
4.3.1 Independent Variables
4.3.2 Dependent Variables
4.4 Procedure
4.4.1 Preparation
4.4.2 Main Session
4.4.3 Post Session

Chapter 5 Results....................53-78
5.1 Data Analysis
5.1.1 Quantitative Analysis
5.1.2 Qualitative Analysis
5.2 Answering Research Questions
5.3 Reflection on Hypotheses
5.3.1 Hypothesis 1
5.3.2 Hypothesis 2
5.3.3 Hypothesis 3
5.4 Areas for Improvement
5.4.1 Structure and Hierarchy
5.4.2 User Interface and Visual Weight
5.4.3 Correctness and Language
5.5 Effect of Context
5.6 Effect of Task Order

Chapter 6 Research conclusion....................79-85
6.1 Discussion
5.2 Design Recommendation
6.3 Limitations
6.4 Future Work
6.5 Conclusion

References

Appendix

1

Introduction

Background | Methodology | Research Outline

1.1 Background

The term "design" encompasses various aspects, each crucial for understanding the profound impact of a design endeavor. Whether perceived as a field of study, a conceptual proposal, or a tangible product, design signifies change. This change can manifest as an improvement to an existing solution, a modification in a product's aesthetics, or an entirely new concept, affecting both physical objects and abstract systems. As Krippendorff & Wester (2005) articulated, design serves as a method of interpreting the world around us. Understanding design as a dynamic process rather than a static outcome shifts our focus to the contexts in which these changes occur. Products do not exist in isolation; they interact with their environments and transform user practices. For instance, the advent of the digital camera revolutionized the way we take and share photographs, illustrating how new designs alter behaviors and social practices. (Kitap et al., 1933)

Successful design goes beyond aesthetics. It demands a deep understanding of how people interact with products within the fabric of their daily lives. User-centered design particularly emphasizes understanding products in relation to their use contexts, focusing on the impact on users' lives (Keinonen and Takala, 2006). Questions about usability, accessibility, and user interaction are paramount, requiring designers to delve deeply into the users' reality. The context of use, broadly defined as the ideas, situations, events, and information related to a product, plays a critical role in shaping design decisions. This context is dynamic, influencing and being influenced by the design. Designers must navigate this complexity, foreseeing the entire situation that arises when a new product is introduced into a social setting.

Video emerges as a particularly suitable tool in this endeavor. It offers rich, detailed material and diverse perspectives, fostering a dialogue between designers and the contexts they explore. As Schoen (1983) noted, this dialogue is increasingly social due to the complexity of modern design environments. Video facilitates this process, enabling designers to capture and analyze the nuanced interactions within use contexts. By immersing themselves in the experiences of the user through video, designers gain valuable insights that inform their decision-making process (Ylirisku & Buur, 2007).

However, simply bringing in more detailed material and greater amounts of information is not enough. Designers must seek different perspectives and see how the pieces of the puzzle may relate to each other in novel ways, as the amount of information in design projects has long exceeded the capacity of individual designers. The inherent wealth of information within video data comes at a cost. Extracting meaningful insights from video footage can be a time-consuming and labor-intensive process. Analyzing hours of video to identify user needs, pain points, and interactions can significantly hinder design workflows (Ylirisku & Buur, 2007).

This is where mind maps come in. Mind maps are visual representations of information that act as a blueprint, capturing the core elements of a video in a structured and easily digestible format. By presenting key concepts and their interrelationships spatially, mind maps allow designers to grasp the essence of a video quickly and efficiently (Sbaa et al., 2022).

This thesis introduces a novel tool that utilizes the power of Large Language Models (LLMs) to automatically generate mind maps from video data for design. This innovative approach leverages the capabilities of LLMs to process both audio and visual information within the video. By analyzing the content, the tool extracts key details and organizes them into a structured mind map. This automation not only streamlines the video analysis process but also frees up valuable time for designers, allowing them to focus on the more creative and analytical aspects of design. Utilizing a mind map is beneficial for expressing and organizing information in a clear and understandable manner (Yang et al., 2016). Consequently, integrating a mind map into our process will help us establish a concentrated study to assess its impact on the design process in terms of time, efficiency, performance, and user preference.

The proposed workflow for designers using the AI-generated mind map (shown in Figure 1) begins with them receiving a brief context to understand the task at hand. They then watch the video to gather initial insights and identify key points. Following this, designers go through the AI-generated mind map, which provides a clear and structured overview of the video, highlighting key concepts in an easily digestible format. This step significantly reduces the time and analytical rigor required for the analysis. Next, designers cross-check the mind map against the video content, questioning the links and connections while adding new ones. This process of validating the LLM's interpretations with their own understanding not only ensures the mind map's accuracy and completeness but also helps designers reframe their understanding and better remember the video contents. Finally, they validate the mind map's utility and relevance, confirming its effectiveness in aiding their design process.

Figure 1: Hypothesis Workflow of the Video Analysis with the mindmap tool (Source : Author)

An user study was conducted involving 28 design practitioners. The participants were tasked with assessing and modifying the mind map within the mind map web tool. Along with examining the hypotheses mentioned earlier, we also assessed the performance of mind maps generated by LLMs in comparison to those created by humans. Specifically, the following research questions were explored:

1. *How do AI-generated mind maps compare to human-generated mind maps in terms of efficiency and effectiveness in aiding video-based design (VBD)?*
2. *What impact do AI-generated mind maps have on the designer's cognitive load, enjoyment, and perceived usefulness compared to human-generated mind maps in aiding VBD?*
3. *What factors influence the effectiveness of AI-generated mind maps in aiding designers' decision-making processes?*

During the experimental study, it was found that designers are positive about integrating the mind map, especially during the initial stages of the design process. Designers pointed out that the mind map is particularly effective in summarizing the content of the video in a structured manner because it directly addresses the root cause of the problem as in a goal-oriented design process. It was also found that our tool was able to reduce the cognitive workload involved in memorizing and reinterpreting the insights from the video, allowing people to focus their energy on the design task. Furthermore, with LLM-generated recommendations, our plugin was able to enhance designers' logic and their ability to articulate insights. However, designers also emphasized the potential consequences of using the AI suggestions irresponsibly and highlighted opportunities to make the AI recommendations more structured and reliable.

In this work, several important contributions are offered:

- *Introduction and study of how practitioners can implement mind maps in the early stages of their video-based design workflow.*
- *A framework to help designers generate their own mind maps and iterate outputs according to their design needs.*
- *Insights about the challenges and opportunities of using AI generated mind map assistance in supporting video analysis tasks.*

By exploring the integration of AI-generated mind maps into the design process, this study aims to contribute to the ongoing discourse on how AI can effectively support human creativity and decision-making in design.

1.2 Research methodology

The thesis is structured around six integral phases, each contributing to the overarching goal of understanding the impact of AI-generated mindmaps on VBD process.

Phase 1 - Literature review
The first step in our research methodology involved conducting a comprehensive literature review. This review aimed to understand the current state of knowledge regarding user-centered design, Video-Based Design (VBD), and the use of mind maps in design processes. We explored various academic articles, books, and case studies to identify key trends, challenges, and opportunities in these areas. By synthesizing this information, we were able to establish a solid theoretical foundation for our study and identify gaps in the existing research that our project aims to address. The literature review also informed the development of our research questions and the design of our study.

Phase 2 - Framing the Research Questions
Based on the insights gained from the literature review, we framed several research questions to guide our study. These questions were designed to explore the impact of mind maps generated by Large Language Models (LLMs) in the VBD process. Overall, we aimed to answer the question, "How do the AI generated mindmaps facilitate video-based designing?".

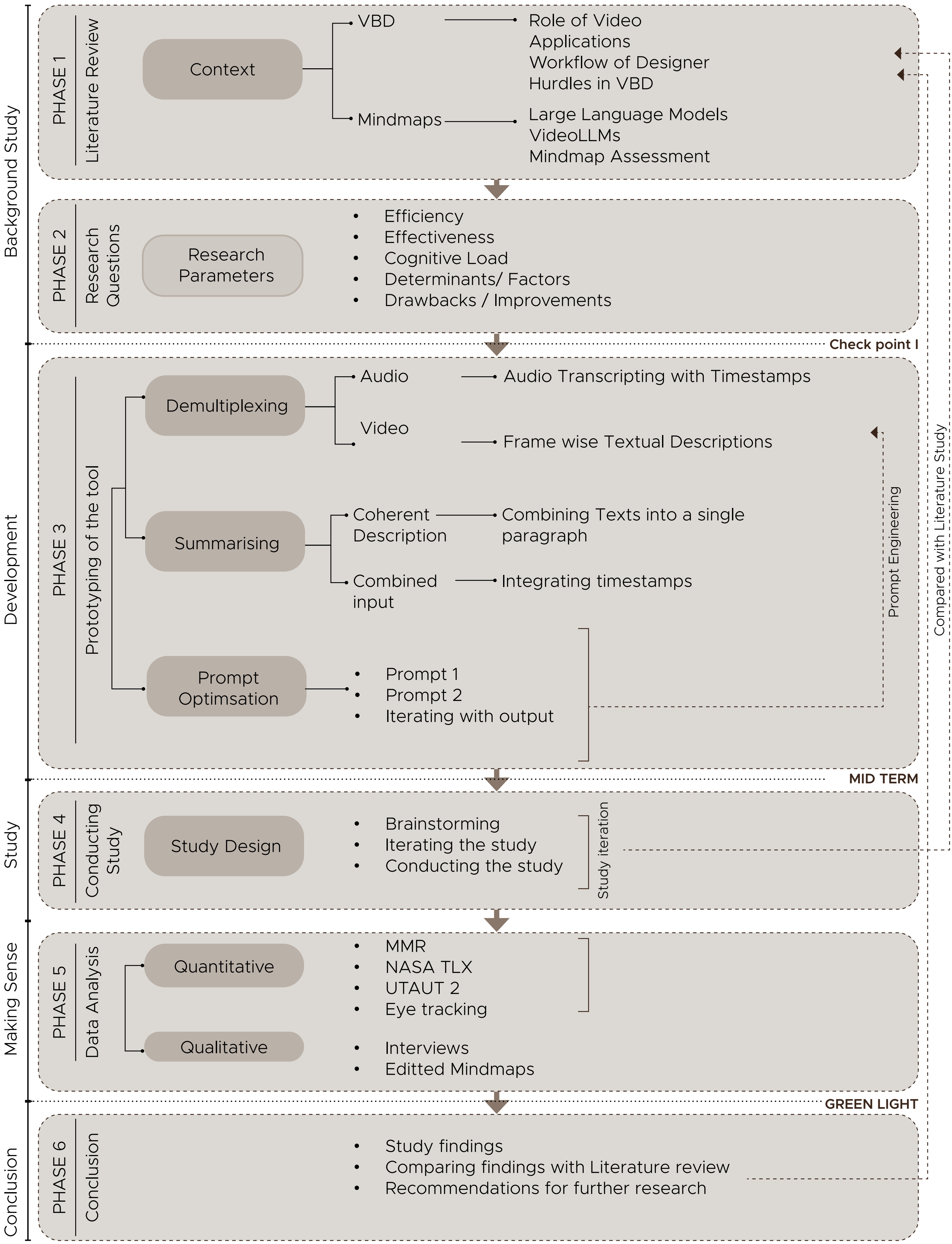
Phase 3 - Prototyping of the Tool
Following the framing of our research questions, we proceeded to prototype a tool capable of generating mind maps from video content. This tool leverages advanced Large Language Models (LLMs) to analyze multimodal video inputs and produce structured, visual representations of key concepts. The prototyping phase involved iterative development and testing to refine the tool's functionality and ensure its usability. By creating a working prototype, we were able to provide a tangible example of our proposed solution, which was crucial for the design and execution of our study.

Phase 4 - Conducting the Study
With the prototype in place, a study was designed to evaluate its impact on the VBD process. The study involved 28 designers who were asked to watch two videos from different contexts and then engage in activities using both LLM-generated and human-generated mind maps. The study design included both quantitative and qualitative methods to capture a comprehensive range of data. Participants' task performance was measured in terms of accuracy, completeness, and efficiency, while their subjective experiences and perceptions were gathered through surveys and interviews. This mixed-methods approach enabled us to gather rich, detailed data on the tool's effectiveness and usability.

Phase 5 - Data Analysis
The data collected from the study were subjected to rigorous analysis to identify patterns, trends, and insights. Quantitative data, such as task performance metrics, were analyzed using statistical methods to determine significant differences between the two types of mind maps. Qualitative data from surveys and interviews were analyzed using thematic analysis to uncover recurring themes and insights into participants' experiences. This combination of quantitative and qualitative analysis provided a holistic understanding of the tool's impact and effectiveness.

Phase 6 - Interpretation
Finally, we interpreted the results of our data analysis to draw meaningful conclusions about the tool's efficacy and potential for improving the VBD process. We compared the performance and usability of LLM-generated mind maps to those created by human designers, identifying key strengths and weaknesses of each approach. Additionally, we considered participants' feedback and suggestions for improvement to inform the next iteration of the tool. Our interpretation of the results was grounded in the context of existing literature and aimed to contribute new knowledge to the field of user-centered design and AI-assisted design tools.

1.3 Project outline



2

Literature Review

Video-Based Design | Mindmap | Human-AI systems

Chapter Overview

The literature review in this document intricately puts together the various facets of video-based design (VBD) and the intrinsic potential of mind maps generated by large language models (LLMs) in facilitating VBD. We start by understanding how VBD is integral to user-centered design (UCD), emphasizing its role in capturing real user interactions and behaviors, which is foundational to creating empathetic and effective designs. This context sets up the study by establishing the importance of video as a rich source of data that informs and enhances the design process.

Next, we delve into what VBD entails, examining why video is such a valuable tool in design. This includes discussing the various contexts and applications where VBD is implemented. By understanding the designer's journey in VBD and the detailed processes involved in interpreting video data, we highlight the complexities and the need for efficient tools to aid in this analysis. This exploration underscores the necessity of our study, setting the stage to evaluate how mind maps can alleviate some of these burdens.

The review then transitions to the hurdles faced in VBD, such as the extensive time commitment and cognitive load required for thorough analysis. Here, we explore mitigation strategies and methods in practice. This section is crucial as it frames the study's aim to evaluate the feasibility of our mind map tool in reducing the analytical rigor required in VBD.

From here, the discussion moves to mind maps and their role in design. We explore how mind maps aid in memory retention and knowledge capture, making them a desirable tool in the design process. By assessing the desirability of mind maps, we set up criteria to evaluate how well they meet the needs of designers. Next, we read about how Large Language Models (LLMs) and VideoLLMs are implemented in existing frameworks to generate mind maps from videos to capture content effectively. We then look at the effectiveness of comparing LLM mind maps with human-generated mind maps to evaluate the viability of the tool in enhancing design workflows. This evaluation forms a core part of our study, as it directly relates to determining whether LLM-generated mind maps can be a reliable and efficient tool for designers.

Finally, we broaden the discussion to the design of human-AI systems for UCD, examining factors that influence their efficiency and the potential pitfalls. This section is pivotal in understanding how to create systems that not only assist designers but also integrate seamlessly into their workflows. By exploring these themes, we prepare to evaluate the overall impact of LLM-generated mind maps on VBD, ensuring our study addresses key aspects of desirability, feasibility, and viability.

Through this narrative, the literature review sets a comprehensive foundation for our study, guiding the reader through the importance of VBD, the challenges it presents, and the potential of mind maps to transform the design process.

2.1. Video-Based Design

2.1.1. Importance of User-centered Design

User-centered design (UCD) differs from traditional design methods by prioritizing human needs and involvement in the design process, as seen in various research papers. UCD and Human-centered Design (HCD) focus on considering users' requirements first, involving them through observation, interviews, and testing (Xu, 2022), (Fotler et al., 2021). These methodologies emerged when computer interfaces were challenging, aiming to create more user-friendly products. In contrast, traditional design methods often overlook user input, leading to products that may not fully meet user expectations or needs. UCD emphasizes creating intuitive and efficient designs by understanding user behaviors and preferences, ultimately enhancing user experience and satisfaction (Kraft, 2012). The Figure 2 illustrates that a successful user experience is achieved by balancing user needs, business goals, and the information provided (Noyes & Cook, 2012). By incorporating UCD principles, developers can better capture customer needs, reduce errors, and improve product quality, aligning with the evolving landscape of intelligent sociotechnical systems (Xu, 2022). Furthermore, the iterative nature of UCD allows for continuous refinement and optimization of products based on real user feedback, ensuring that the final design truly resonates with the target

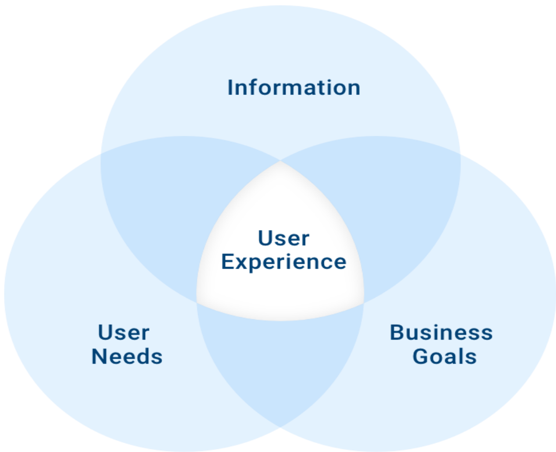


Figure 2: User centered Design Approach (Source : Noyes & Cook, 2012)

2.1.2. The Role of Video-Based Design in User-Centred Design

Video-based designing involves using video recordings as a tool to observe, analyze, and understand how people interact with products, services, or environments, which helps designers create better solutions that meet users' needs and preferences (Ylirisku & Buur, 2007).

This method includes capturing real-life scenarios and user behaviours on video, which can then be reviewed and studied in detail to gain insights into user experiences and challenges. The process of video-based designing can vary significantly, with some methods focusing on the sequence of activities, while others emphasize collaboration and the skill of staging and framing the video content (Ylirisku & Buur, 2007).

Video-based designing is crucial for user-centred design because it provides a rich, detailed view of how users interact with products in their natural environments, which helps designers understand the context and nuances of user behaviour. The use of video in design helps in creating a more conscious user-centered design practice, where designers can collaboratively learn and become inspired by the user's reality, leading to more effective and user-friendly design solutions. A firmly based understanding of the use context helps ensure that designs will fit into users' reality (Ylirisku & Buur, 2007).

2.1.3. The Value of Video and Non-Verbal Cues in Design

- *Rich Contextual Information:* Video captures real-life scenarios and user behaviours in their natural environments, providing a rich, detailed view that helps designers understand the context and nuances of user interactions better than static images or text descriptions (Ylirisku & Buur, 2007).
- *Enhanced Observation of Non-Verbal Cues:* Videos allow designers to observe subtle details and non-verbal cues, such as body language and facial expressions, which are often missed in traditional research methods like interviews or surveys. Video stories may illustrate how multi-faceted and complex even simple real-life tasks may be (Ylirisku & Buur, 2007).
- *Engaging and Memorable:* The process of creating and watching videos can be more engaging and memorable for both designers and participants, leading to a deeper understanding and retention of the observed behaviours and interactions.
- *Collaborative Analysis:* Video recordings can be reviewed multiple times and shared with team members, facilitating collective analysis and discussion, which helps in generating more comprehensive insights and design ideas (Ylirisku & Buur, 2007).
- *Real-Time Feedback:* Videos provide real-time feedback on how users interact with a product, allowing designers to see immediate reactions and make necessary adjustments quickly, which is more efficient than waiting for written reports or feedback forms (Ylirisku & Buur, 2007).
- *Visual Storytelling and Influence on Creators:* Videos can tell a story about the user's experience, making it easier for designers to communicate their findings and design concepts to stakeholders, clients, and team members compellingly and understandably. Moreover, the process of making and reviewing video artefacts can lead to new insights and ideas for designers, as they become more aware of the user's reality and the impact of their design decisions (Ylirisku & Buur, 2007).

By using video, designers can ensure that their solutions are truly aligned with the needs and behaviours of their users, leading to more successful and satisfying products and services.

2.1.4. The Role of Video in Design

Understanding the dual roles of video as both 'designer glue' and 'designer clay' is crucial for designers in the user-centered design process.

On one hand, video acts as "designer glue" by fostering collaboration between diverse stakeholders in a project, glueing designers together. It helps bridge the gap between perspectives, promoting a sense of shared ownership and involvement throughout the design journey. Video also excels at creating a unified vision. By capturing and sharing user stories in a compelling format, designers can ensure consistency and coherence even in complex projects with multiple stakeholders and extended timelines. Furthermore, video enhances communication by visually conveying intricate ideas and user experiences that might be challenging to articulate solely through words. This visual clarity keeps everyone on the same page, minimizing misunderstandings and ensuring all team members are aligned with the overall vision (Ylirisku & Buur, 2007).

On the other hand, video transforms into "designer clay," offering a flexible platform for exploration, fluid like and can be shaped like clay. Designers can experiment with various ideas and concepts in a fluid and iterative manner. Video allows for real-time feedback and facilitates adjustments on the fly, enabling an agile design approach. Beyond boosting internal innovation, video can capture user interactions with prototypes or existing products. These recordings provide invaluable insights into user behavior and preferences, which can then be directly molded into the design to create a product that resonates more effectively with the target audience. Finally, the very process of creating and editing video can spark creativity among designers. It pushes them to think outside the box and explore unconventional ways to present and solve design challenges, ultimately leading to more innovative and user-centric solutions (Ylirisku & Buur, 2007).

By seamlessly integrating the functionalities of "designer glue" and "designer clay," video becomes an essential tool within the user-centered design process.

2.1.5. Applications of Video Based Design

1. ***Interaction Analysis***

By meticulously examining video recordings of user interaction with products or environments, designers gain valuable insights into user behavior's nuances. This analysis allows for a more comprehensive understanding of user difficulties and opportunities for improvement in design solutions. Techniques like interaction analysis, which involve detailed examination of recordings to identify non-verbal cues and subtle user interactions, further enhance this process solutions (Ylirisku & Buur, 2007).

2. ***Design Ethnography***

Immersing oneself in users' natural environments through video observation is another crucial application. Ethnographic methods, such as shadowing users, conducting situated interviews, and utilizing self-recordings, provide rich contextual information about user needs and behaviours. This approach, captured through video, informs the design process by revealing the "why" behind user actions (Ylirisku & Buur, 2007).

3. ***Usability Tests in Video-Based Design***

Video recordings of users interacting with prototypes or products in usability tests offer invaluable data for designers. This application, facilitated by usability testing, allows for visual evidence of user successes and struggles. By analyzing these recordings, designers can pinpoint areas for improvement and ultimately enhance the overall user experience (Ylirisku & Buur, 2007).

Additionally, workflows like co-editing and co-creation involve collaborative video creation with users and stakeholders, fostering a shared understanding and a sense of co-authorship in the design process. The Video Card game (shown in Figure 3) is one effective method to discuss about a video in a collaborative setting (Ylirisku & Buur, 2007). Furthermore, video can be used for video brainstorming to capture and explore creative ideas during collaborative design sessions. This allows for rapid visualization and iteration of design concepts. Scenario scripting workflow involve creating and recording potential user interactions with a product or service, helping designers identify and address usability issues early in the design process. Figure 4 below shows the enactment of a deaf person phoning his friend during a workshop. Finally, video can be a powerful communication tool. Video stories and portraits allow designers to share user experiences in a compelling and understandable format for stakeholders. These methods can be particularly effective in communicating research findings and design concepts (Ylirisku & Buur, 2007).

Figure 3: Design team engaged in Video card game (Courtesy : Ylirisku & Buur, 2007)

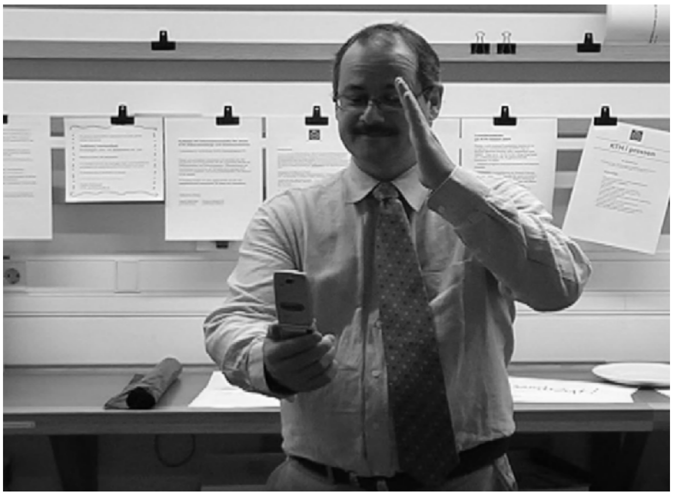


Figure 4: Phoning a Deaf person enactment for Video (Courtesy : Ylirisku & Buur, 2007)

2.1.6. Unveiling Insights : A Video Analysis Journey

The grounded co-thinking process is similar to the American Philosopher John Dewey's concept of reflective thinking (Kitap, Değerlendirmeleri, Dewey, 1933), which involves a careful and systematic approach to problem-solving by reflecting on experiences and observations to derive insights and solutions. In the context of video-based design (VBD), grounded co-thinking refers to the cognitive steps that designers undertake to derive insights and solutions from user interactions captured on video. These steps—exploring, describing, and relating—are essential for making sense of complex user data and translating it into actionable design decisions (Ylirisku & Buur, 2007). The three activities that are deeply interconnected and help in understanding and solving design problems by continuously reflecting on and refining ideas.

- *Exploring:* Exploring involves investigating and understanding the various aspects of a subject without following a fixed protocol, allowing for flexibility and the possibility of shifting focus as new insights are encountered. This phase emphasizes the ability to challenge current views and adapt to new directions, making it a dynamic and open-ended process. For example, in design research, exploring might involve observing users in their natural environment to gather raw data about their interactions with a product or service (Ylirisku & Buur, 2007).

- *Describing:* Describing is the process of detailing and articulating the findings from the exploration phase, often through narratives, visual representations, or other forms of documentation. This step is crucial for making sense of the collected data and communicating the insights to others, such as team members or stakeholders. In the context of video in design, describing might involve creating video stories or portraits that capture and convey the essence of user experiences (Ylirisku & Buur, 2007).

- *Relating:* Relating involves connecting the insights and descriptions to broader concepts, theories, or frameworks, thereby situating the findings within a larger context. This step helps in understanding how the specific insights fit into the bigger picture and can inform future design decisions or research directions. For instance, relating might involve comparing the observed user behaviors with existing design principles to identify areas for improvement or innovation (Ylirisku & Buur, 2007).

The video-based design (VBD) journey involves capturing and analyzing real-life user interactions to derive valuable insights (Ylirisku & Buur, 2007). For better understanding, we categorize these cognitive steps alongside the known steps of the user journey, seamlessly integrating the grounded co-thinking process into the design workflow. Figures 5 and 6 combinedly depicts the user journey of the designer involved in video analysis tasks.

1. Explaining

1.1 Recording the Video: The first step involves capturing videos of users interacting with a product or service in their natural environment, which provides a rich source of data that captures real-life contexts and behaviors.

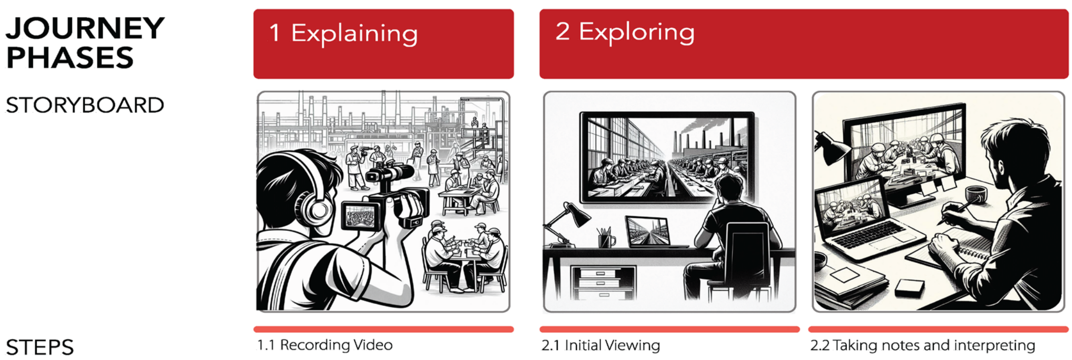


Figure 5: Designer Journey Map of Video Analysis (Source : Author)

2. Exploring

2.1 Initial Viewing: Designers watch the recorded videos multiple times to get a general sense of the interactions and to start identifying any obvious patterns or behaviours that stand out. This initial viewing is crucial for familiarizing oneself with the data.

2.2 Taking Notes and Interpreting: During this phase, designers start taking detailed notes and interpreting the interactions. Designers must interpret the information from the videos, which involves understanding the complex and layered interactions that occur, much like how anthropologists' study and make sense of cultural practices in their ethnographic research. This involves understanding complex and layered user behaviors, akin to how anthropologists study cultural practices in ethnographic research. Interpretation may deeply affect later activities by guiding what is seen as important, in what direction ideas will be developed, and what activities will be supported by the designs.

3. Describing and Relating

3.1 Finding Focus: During the detailed analysis, designers focus on specific moments or interactions that seem particularly significant or revealing. These focal points help in narrowing down the vast amount of data to the most relevant parts that can provide valuable insights.

3.2 Collaborative Analysis: Often, the video is analyzed by a team of researchers who discuss their observations and interpretations together. This collaborative approach ensures that multiple perspectives are considered, leading to a more comprehensive understanding of the user interactions. This is where the collaborative process of interpretation provides its value. When different observations become the subject of discussion within a design team, these differences are brought to light. Shared interpretations help a design team open new perspectives in looking at the material and find new opportunities for design. Interpretations are in this respect like "concepts" (Blumer & Shepherd, 1970).

3.3 Rating: A critical component of this phase is rating the identified focal points. Rating involves evaluating and prioritizing the significance of each focal point to determine which insights or actions are most important or desirable for further analysis and design development. This decision can be made individually by each team member or collaboratively through discussion. The rating process is crucial as it helps in filtering the most impactful data from the vast amount of collected information, ensuring that the design process is focused and effective. After rating, designers choose the appropriate tools or methods to analyze or present the data effectively.

4. Reporting Results

4.1 Creating Video Artefacts: After interpreting the video data, designers need to translate their findings into new forms, such as design concepts, prototypes, or user stories, to communicate their insights and ideas effectively to the rest of the design team and stakeholders. Designers use methods such as video stories, video portraits, and video collages to present their findings in a compelling and understandable way. These artefacts help in communicating the insights to stakeholders and guiding the design process.

4.2 Iterative Process: The insights gained from the video analysis are continuously integrated into the design process. Designers test and refine their designs based on real user feedback and interactions, ensuring that the final product is both functional and user-friendly.

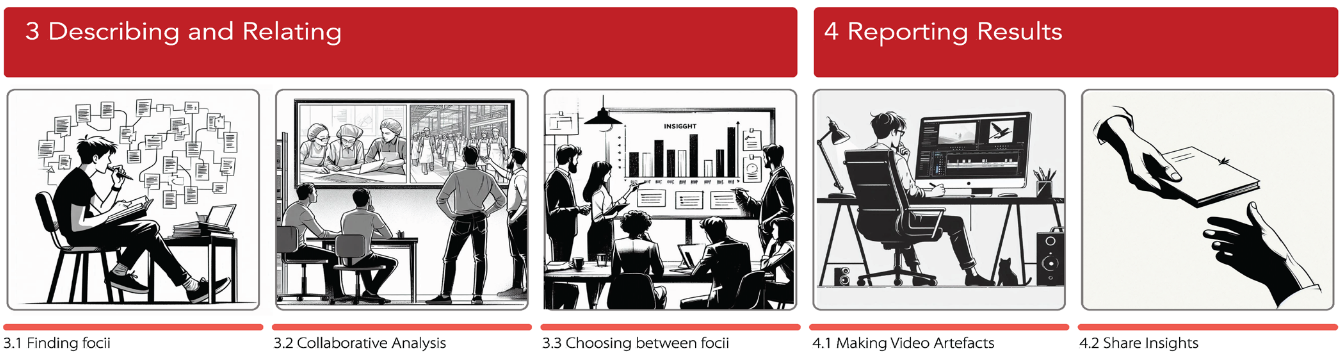


Figure 6: Designer Journey Map of Video Analysis (Source : Author)

2.1.7. Hurdles in VBD

1. Lack of different perspectives

Seeing things from a new perspective is crucial to finding radically new opportunities for design. Different perspectives bring diverse ideas and solutions to the table, which can significantly enhance creativity and innovation in the design process, leading to more effective and user-friendly products. Different perspectives can help uncover subtle issues and opportunities for improvement that might not be evident through a single viewpoint, leading to a more thorough and effective design process. When gathering input from multiple perspectives, designers often face data overload, making it challenging to sift through and identify the most relevant insights, which can be time-consuming and overwhelming. Coordinating and integrating the observations and interpretations of various team members can be difficult, leading to potential miscommunications and delays in the design process. For most people it comes as a pleasant surprise when they realise how many other observations and interpretations in addition to their own are possible – at least once they get over the painful revelation that their way of seeing things is not the only one and may not be the "right" one. This clash of views immediately triggers discussion (Ylirisku & Buur, 2007).

2. Problem of Bias

By understanding and addressing these sources of bias, designers can improve the accuracy and reliability of their video-based design processes, leading to more effective workflows and user-centered outcomes. Bias in participant behavior occurs when participants, aware they are being recorded, alter their behavior to appear more favorable or socially acceptable, resulting in data that does not accurately reflect their natural actions and interactions. Additionally, selective recording and editing can introduce bias as designers might unintentionally focus on aspects of the video data that align with their expectations or hypotheses, skewing the analysis and final design decisions. Interpretation bias also plays a role, as different team members may interpret the same video data differently based on their backgrounds, experiences, and expectations, leading to biased conclusions that can affect the overall design process. Addressing these biases is crucial for enhancing the validity and reliability of the insights derived from video-based design methods (Ylirisku & Buur, 2007).

But, how can we mitigate bias?

1. Blind Analysis:

Implementing blind analysis, where the person analyzing the video data is unaware of the specific research questions or hypotheses, can help reduce bias by ensuring that the analysis is more objective and less influenced by expectations. By not knowing the specific goals of the study, the analyst can focus purely on the data itself, which helps in reducing the risk of interpreting the data in a way that confirms preconceived notions or desired outcomes. To implement blind analysis, the video data is often anonymized or stripped of contextual information that might hint at the research objectives. The analyst then reviews the video, noting behaviours, interactions, and other relevant details without any preconceived ideas about what they should find. This helps in capturing a more genuine and comprehensive understanding of the user experience. For example, in a study focusing on parent-child interactions, the blind analysis might involve an analyst reviewing video footage of family routines without knowing the specific behaviors or interactions the researchers are interested in (Ylirisku & Buur, 2007).

2. Multiple Perspectives:

Involving multiple team members with diverse backgrounds in the analysis process can help mitigate bias by providing a range of interpretations and reducing the influence of any single perspective. This diversity ensures that the analysis is not dominated by a single viewpoint, which can lead to a more comprehensive and balanced understanding of the data. Team members from different disciplines and with varying experiences can highlight different aspects of the video data, question underlying assumptions, and bring attention to potential blind spots that might otherwise be overlooked. This collaborative approach encourages critical discussion and debate, fostering a more rigorous and nuanced analysis (Ylirisku & Buur, 2007).

3. Time and Effort Intensive Nature of Video-Based Design

Analyzing video data for design purposes is inherently time-consuming due to the necessity of viewing extensive footage to capture relevant details, which becomes even more challenging with longer or multiple videos. The effort required in video-based design is significant, as it involves not just watching the videos but also interpreting and coding the data to identify and categorize behaviors, interactions, and other pertinent elements. Interpreting video data is complex and demands a high level of engagement and critical thinking to understand subtle nuances and context-specific behaviors. Blumer (1986) emphasizes that a critical mistake in studying social life is to let prior concepts and beliefs substitute for firsthand experience, noting that sound and insightful interpretations require time and patience, which are often lacking in projects, especially where time efficiency and cost reduction are crucial. It is commonly cited that meaningful insights can take up to 60 times the duration of the video, implying that each minute of video might require an hour of analysis. Structured methods like Interaction Analysis Lab, Video Card Game, and Video Stories can streamline this process by providing clear frameworks for analysis, thereby reducing the required time and effort. Additionally, involving the entire group in exercises such as post-it or sketching can reduce the workload on one single person, and while video interaction analysis with a mixed team can be engaging and bring unexpected perspectives, it can also be quite exhausting (Ylirisku & Buur, 2007).

4. Cognitive Load and Attention Span

Various factors affect the attention of designers as they analyze and interpret video footage. Limited attention span makes it hard to sustain concentration for more than two hours, as our brains naturally struggle to focus on a single task for extended periods without breaks. Video-based design demands high levels of attention because designers need to watch and re-watch footage to capture all relevant details, which can be mentally exhausting and lead to decreased focus over time, particularly with long or complex footage. Attention levels can vary significantly depending on the project's relevance and interest to the individual, as people are naturally more engaged when working on tasks that align with their interests and passions (Ma et al., 2016). Personal interests also greatly influence attention, as individuals are more likely to stay concentrated and motivated when the video's content resonates with their hobbies, preferences, or professional goals. Additionally, the context in which the video is analyzed plays a crucial role in maintaining attention; a familiar and comfortable environment can help individuals stay focused and reduce distractions (Ma et al., 2016). Interpretation functions as the glue that binds together realism and fiction—observations and visions. The fundamental paradox in design interpretation is that it needs to build on both what exists and what does not yet exist, making the process both challenging and exciting. Moreover, designers constantly working under heavy time pressures in industrial projects heightens this challenge to an almost absurd level (Ylirisku & Buur, 2007).

5. Making artefacts

Making artefacts requires a delicate balance between thorough analysis of the video material and creative interpretation to ensure that the final product effectively communicates the intended message or design concept. Video artefacts link field data to design ideas, inform about what is relevant, generalise findings by combining data, help to empathise with people, and focus design by directing the interest. They also help evaluate designs in the later phases of the project. One major hurdle is the time and effort required to create high-quality video artefacts, as it involves not just recording but also editing and post-processing it to share with others. Making video artefacts to highlight useful insights requires a careful and systematic approach, as misinterpretation of the data can lead to incorrect conclusions and design decisions, making it crucial to have a clear framework for analysis.

2.2. Mitigating Hurdles in VBD : Exploring AI Generated Mind maps

2.2.1. Intoduction to Mind maps

Mind maps, a graphical technique for organizing information, can vary significantly in structure and complexity. Typically, a mind map consists of a central concept with branches radiating outwards, each representing a subtopic or related idea (Sbaa et al., 2022). The basic structure includes nodes (representing ideas or concepts), edges (connections between nodes), and sometimes clouds or graphical connections to group related nodes (Siochos, V., & Papatheodorou, C., 2011). Mind maps can be simple, with an average of 31 nodes, each containing one to three words (Beel & Langer, 2011). A hierarchical mind map is a structured visual representation of information that organizes concepts in a top-down manner, starting from a central idea and branching out into subtopics and further details. The key components of a hierarchical mind map include nodes, which represent individual concepts or pieces of information, and edges, which connect these nodes to illustrate relationships and hierarchies. The central node, or parent node, is the core idea from which all other nodes, or child nodes, diverge. These child nodes can further branch out into sub-nodes, creating multiple levels of hierarchy that reflect the depth and complexity of the subject matter (Chen, 2020)

2.2.2. Using Mind Maps to Capture Video Content

Mind maps can be effectively used to capture the content from a video, providing a structured and intuitive way to organize and visualize information. Mind maps facilitate the breakdown of complex video content into manageable segments, making it easier to understand and retain information. For instance, VideoMap employs a map metaphor to visualize video content hierarchically, allowing users to explore and annotate video data interactively, akin to reading a map (Ma et al., 2016), (Yang et al., 2016). This approach not only aids in summarizing and revealing important features and events in videos but also supports semantic zooming and path navigation through sketch gestures, enhancing the interactive exploration experience (Yang et al., 2016). Furthermore, mind maps are valuable in knowledge management systems, where they help convert tacit knowledge into explicit knowledge, making information more accessible and easier to share within organizations. In the realm of cognitive neuroscience, techniques like Mind-Video leverage brain activity data to reconstruct visual experiences, demonstrating the potential of mind maps in capturing and interpreting complex visual information from videos (Chen et al., 2023). Overall, the integration of mind maps with video content not only enhances comprehension and retention but also supports interactive and scalable exploration, making it a powerful tool for both educational and professional applications.

2.2.3. Effectiveness of Large Language Models in generating Mindmaps

Language models have shown promise in aiding the generation of mind maps, which are valuable tools for organizing information and enhancing learning processes (Kadagidze, 2016). Research indicates that brain and language model activations exhibit structural similarities, allowing for partial mappings between neural recordings and computational language models (Karamolegkou et al., 2023).
The papers highlight the importance of evaluating LLMs in different knowledge fields to uncover potential weaknesses like hallucinations (Puchert et al., 2023), assess their planning capabilities in autonomous, heuristic, and human-in-the-loop modes (Karthik et al., 2023), and explore the integration of LLMs with Knowledge Graphs (KGs) to enhance knowledge representation and reasoning (Pan et al., 2023). While LLMs excel in natural language processing tasks, their effectiveness in creating mind maps may depend on the specific requirements of the task and the structured nature of the information involved. Further research focusing on LLMs' ability to generate visual representations like mind maps could provide valuable insights into their broader cognitive capabilities beyond text-based tasks.

2.2.4. Effectiveness of Mind Maps in Enhancing Learning and Memory Retention

Mind maps have proven to be highly effective in enhancing student learning and retention across various subjects. They facilitate a non-linear, visual organization of information, which is particularly beneficial for students with a visual learning preference or learning disabilities, as it helps them concentrate and understand information better (Palaniappan et al., 2023). In medical education, mind maps have been shown to significantly improve students' understanding and retention of complex topics like the morphology of skin lesions, with students in the mind mapping group outperforming those in traditional lecture-based learning (Palaniappan et al., 2023). Similarly, in the context of higher education, mind maps help students synthesize theoretical and practical material, aiding in better diagnosis and decision-making skills. The technique also enhances information retrieval and long-term retention, as evidenced by studies on medical students where mind mapping led to higher post-test scores and better information retention after one month compared to traditional methods (Negalur et al., 2022). In primary education, mind maps have been effective in improving vocabulary retention among young learners, demonstrating their versatility across age groups (Ngoc, 2023). Furthermore, mind maps combined with multimedia technology in college settings have been shown to help students master important and difficult knowledge more efficiently, fostering systematic and creative thinking (Guo, 2021). They also support the flipped classroom model by helping students connect fragmented knowledge points and promoting active learning (Zuo & Gu, 2022).

Interactive mind maps, which allow users to focus on specific nodes while hiding others, can reduce information overload and enhance the viewing experience. Furthermore, mind maps facilitate collaborative learning, fostering positive interactions and comprehensive memorization among students (Bo, 2017). When viewers interact with mindmaps, such as clicking on nodes to reveal more information, it engages them actively in the learning process, which can enhance their retention of the video content by making the learning experience more interactive and engaging (Bo, 2017). The visual and interactive nature of mindmaps can enhance recall by providing visual cues and a clear structure that helps viewers remember the content more effectively, as they can easily recall the visual layout and the connections between different parts of the content (Bo, 2017). Mind maps focus on extracting and organizing key phrases and keywords from video lectures, which helps students to concentrate on the most important points and reduces the cognitive load associated with processing large amounts of information (Vimalaksha et al., 2019). The development of software tools that automatically generate mind maps from video lectures can streamline the creation process, making it easier for students to engage with and retain video content (Vimalaksha et al., 2019). Different colors in a mind map were found to improve information recall, facilitate quicker access to information, and boost creativity (D'Antoni et al., 2009).

One of the main challenges in using mind maps for learning is that creating an effective and comprehensive mind map can be complex and time-consuming, especially for beginners who may not be familiar with the best practices for organizing information visually. While there are various applications available to create mind maps, not all students and teachers are comfortable using these digital tools, which can hinder the effective implementation of mind mapping in learning environments (Anggy et al., 2022).

2.2.5. Using Mindmaps to Capture Video Content

Yes, mindmaps can be effectively used to capture the content from a video using Large Language Models (LLMs). The integration of LLMs with video content analysis is demonstrated through various innovative frameworks and methodologies. For instance, the VideoLLM framework leverages the sequence reasoning capabilities of pre-trained LLMs from natural language processing (NLP) to understand video sequences by converting inputs from various modalities into a unified token sequence, which is then processed by a decoder-only LLM to handle diverse video understanding tasks (Chen, G. et al., 2023). Similarly, the Semantic Pyramid AutoEncoder (SPAE) enables frozen LLMs to perform both understanding and generation tasks involving non-linguistic modalities such as images or videos by converting raw pixels into interpretable lexical tokens, thus translating visual content into a language comprehensible to the LLM (Yu et al., 2023). Additionally, the X-LLM framework aligns multiple frozen single-modal encoders and a frozen LLM using X2L interfaces to convert multimodal information into languages, facilitating the integration of multimodal capabilities into the LLM (Chen, F. et al., 2023). These approaches highlight the potential of LLMs to transform video content into structured, interpretable formats, which can be further organized using mindmaps. Mindmaps can visually represent the hierarchical and relational structure of the extracted content, making it easier to comprehend and analyze. Moreover, the use of LLMMaps for stratified evaluation of LLMs' performance in different subfields of knowledge further supports the idea of using mindmaps to capture and visualize complex information (Puchert et al., 2023). Moreover, in the context of education, mind maps can assist in creating course content by leveraging LLMs to generate high-quality learning materials with reduced human involvement, thereby expediting content creation without compromising accuracy or clarity, which is particularly beneficial for adult learning and upskilling initiatives (Leiker & Cukurova, 2023). Therefore, by leveraging the advanced capabilities of LLMs in multimodal understanding and sequence reasoning, mindmaps can serve as an effective tool to capture and organize the content from videos, enhancing both comprehension and analysis.

2.2.6. Method To Evaluate The Generated Mind maps : Holistic Scoring

Various rubric methods have been developed to evaluate mind maps, each with its strengths and limitations. The Mind Map Scoring Rubric (MMSR) developed by Cheng Hua and Stefanie A. Wind incorporates many-facet Rasch modeling to ensure acceptable psychometric properties, making it a robust tool for evaluating mind maps across different educational levels (Hua & Wind, 2018). The MMAR (Mind Map Assessment Rubric) consists of 6 variables - concept-links, crosslinks, hierarchies, examples, pictures, and colors - to evaluate the quality of a mind map and assign a numerical score for comparison purposes (D'Antoni et al., 2009). The structural rubric, which focuses on the number of topics, connections, and hierarchical organization, has shown moderate inter-rater reliability and is useful for assessing the structural integrity of mind maps (Zvauya et al., 2017). The holistic qualitative mind map rubric scoring method evaluates mind maps by considering the overall quality and coherence of the entire map rather than breaking it down into individual components. This method involves judges analytically assessing the mind map as a whole, focusing on the depth of understanding, creativity, and the logical flow of ideas presented. Unlike structural rubrics, which score based on specific elements like the number of nodes and links, the holistic approach captures the nuanced and integrative aspects of a student's knowledge representation (Hua & Wind, 2018). This method is advantageous because it allows for a more comprehensive evaluation of the student's conceptual understanding and creativity, which are often missed by more rigid, component-based scoring systems (Hua & Wind, 2018). Holistic scoring is particularly effective in capturing changes in knowledge structure, as it does not assume a hierarchical arrangement of concepts, making it suitable for diverse and complex mind maps (Watson et al., 2015). Additionally, holistic rubrics have shown higher inter-rater reliability compared to qualitative rubrics, indicating more consistent scoring among different evaluators (Hua & Wind, 2018). This method also aligns well with the evaluators' perceptions of important factors such as accuracy and proficiency, which are crucial in performance assessments (Yune et al., 2018). Furthermore, holistic scoring can be more efficient, as it requires less time to evaluate the overall quality rather than counting individual components, making it practical for large-scale assessments (Tomas et al., 2019).

2.3. Designing Human-AI Co-Creative Systems

2.3.1. Determinants Influencing the Effectiveness of Human-AI Co-Creation Systems

The effectiveness of a human-AI co-creative system is influenced by several determinants, including interaction design, communication dynamics, and user engagement. Effective interaction design is critical, as it shapes the turn-taking, contribution type, and overall communication between human and AI partners, which are essential for a productive co-creative process (Rezwana & Maher, 2022), (Maher & Rezwana, 2022). Communication dynamics, particularly AI-to-human communication, significantly enhance user engagement and the collaborative experience, making the AI appear more reliable, personal, and intelligent (Gmeiner et al., 2022).

Trust and reliance also play pivotal roles in the effectiveness of these systems. Appropriate trust ensures that users know when to rely on AI outputs and when to override them, which is crucial for the proper usage and adoption of AI systems (Bansal et al., 2022). However, trust and reliance must be clearly distinguished; trust is an attitudinal measure, while reliance is behavioural. Misinterpreting these can lead to ineffective human-AI interactions (Scharowski et al., 2022). The Dunning-Kruger Effect (DKE) can also hinder appropriate reliance, as individuals who overestimate their abilities may under-rely on AI, affecting team performance (Gaole et al., 2023).

Under-reliance and overreliance play crucial roles in human-AI co-creation systems, impacting the overall performance of decision-making teams. Overreliance, where individuals agree with AI systems even when incorrect, poses a significant threat to team performance (Vasconcelos et al., 2023). Surprisingly, providing explanations for AI predictions does not always reduce overreliance, as individuals strategically choose whether to engage with these explanations based on costs and benefits. On the other hand, under-reliance, observed when individuals overestimate their performance and thus underutilize AI systems, can hinder optimal team performance as well (Gaole et al., 2023). Studies have shown that overreliance is not always reduced by AI explanations, as individuals strategically choose whether to engage with these explanations based on factors like task and explanation difficulty, highlighting the complexity of reliance dynamics in human-AI interactions (Vasconcelos et al., 2023).

Addressing these issues requires interventions like tutorial interventions to calibrate self-assessment and facilitate appropriate reliance on AI systems, highlighting the importance of understanding and mitigating cognitive biases in human-AI decision-making processes, although they may have mixed effects depending on the user's initial self-assessment accuracy (Gaole et al., 2023). Finally, framing human-AI collaboration as a learning problem and incorporating team learning strategies can further enhance collaboration quality and effectiveness (Kim & Maher, 2023). Thus, a combination of well-designed interaction models, effective communication, appropriate trust and reliance, and learning support mechanisms are key determinants of the effectiveness of human-AI co-creative systems.

2.3.2. Potential Pitfalls in Integrating AI Systems in Human Centered Design

The integration of AI into human-centered design processes presents several potential risks that need careful consideration. One significant risk is the lack of explainability in AI systems, which can undermine trust and reliability, especially when AI fails to perform tasks successfully (Schoenherr et al., 2023). Another major challenge is the lack of effective communication between AI and human users, as many existing systems only allow one-way communication from humans to AI, limiting the AI's potential to be perceived as a true partner (Rezwana & Maher, 2022), (Rezwana & Maher, 2022, Identifying). Another pitfall is the ethical concerns that arise from the AI's role in co-creation, such as issues of trust, reliability, and the potential for AI to overshadow human creativity (Rezwana & Maher, 2022, Identifying), (Rezwana & Maher, 2023). Additionally, varying degrees of AI agency can lead to user frustration, especially when the AI takes too much control or makes decisions that conflict with the human user's intentions (Larsson et al., 2022). The integration of emotional feedback mechanisms is another complex area, as it requires the AI to accurately perceive and respond to the user's cognitive and emotional states, which can be challenging to implement effectively (Abdellahi et al., 2020).

Furthermore, the learning curve associated with using co-creative AI systems can be steep, and users may need support to learn how to collaborate effectively with these systems, similar to team learning strategies used in human-human collaborations (Gmeiner et al., 2022). Lastly, there are broader implications for creative practices, as the introduction of AI into creative processes can lead to unintended side effects, such as dependency on AI-generated content or the erosion of traditional creative skills (Buschek et al., 2021). The potential existential threat posed by Artificial General Intelligence (AGI) further underscores the need for Human Factors and Ergonomics (HFE) to be embedded throughout the AI lifecycle to manage risks and ensure ethical and safe design (Salmon et al., 2023). Moreover, the ambiguity in defining and evaluating human-centered AI (HCAI) complicates the integration process, necessitating greater collaboration between AI and HCI researchers to establish clear guidelines and constructs (Capel & Brereton, 2023). Finally, the focus on intelligence augmentation (IA) rather than solely on autonomous AI highlights the importance of designing systems that augment human capabilities while maintaining ethical standards and interpretability (Zhou et al., 2023). Addressing these pitfalls requires a holistic approach that considers user engagement, ethical concerns, communication dynamics, and the balance of control between human and AI collaborators.

3

System Design

Framework | Prompts | Interface

Chapter Overview

This section explains the innovative LLM-powered mind map plugin created to enhance video design workflows by automatically producing mind maps that highlight important concepts, themes, and relationships in a video. Emphasis was placed on minimalistic design to test initial ideas about integrating mind maps into the design process, resulting in a minimalist user interface and colourless mind maps.

For this study, the mind map visualization tool was deployed online at https://tianhao1997.github.io/LLMmindmap/mindmap.html. This allows users to access and interact with the mind map from any device with an internet connection. In contrast, the AI software responsible for video processing and JSON generation is run locally on a PC situated at the COALA lab. This separation reflects a common design pattern where computationally intensive tasks are handled on dedicated machines, while the user interface remains accessible online.

3.1 Data Input and Processing: Extracting Meaningful Information

This section details the data processing pipeline employed by the LLM-powered mind map plugin to generate mindmaps, as illustrated in Figure 7.

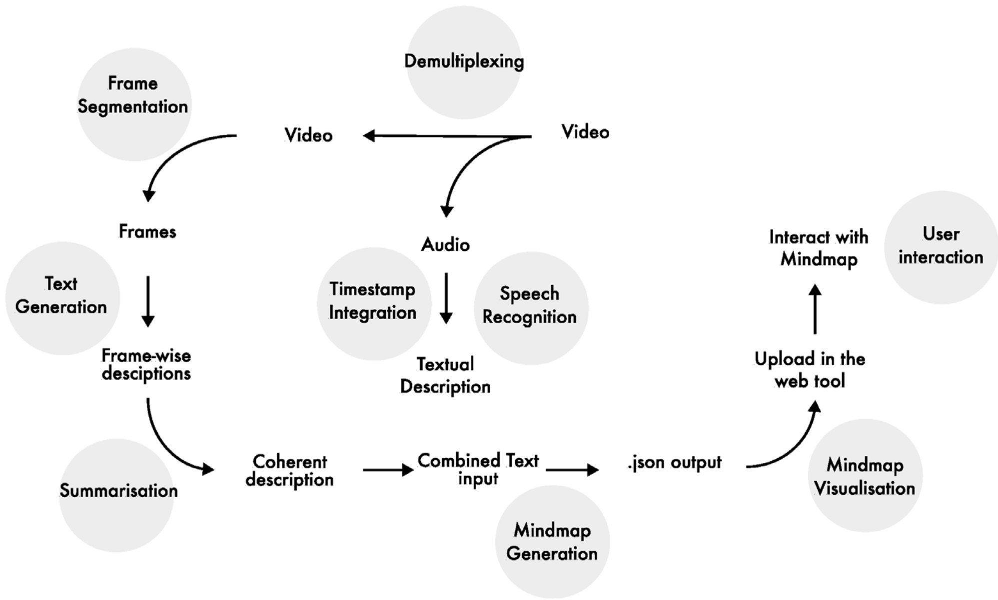


Figure 7: Framework of the System (Source : Author)

1. Preprocessing and Feature Extraction:

Video Segmentation: The plugin first splits the input video into separate audio and video streams.
Frame Extraction: The video stream is further divided into individual frames, essentially creating a series of still images representing the video content.

2. Frame-Level Analysis:

Non-Instructional Text Generation: A non-instructionally tuned GPT-4.0 Turbo model is employed to generate textual descriptions for each extracted video frame (OpenAI, 2023). This model focuses on capturing the content of the frame without requiring specific prompts or instructions.

3. Textual Integration and Summarization:

Prompt-based Integration: The frame-wise text descriptions are fed back into GPT-4.0 Turbo with a specific prompt (Prompt 1). This prompt instructs the model to combine the individual descriptions into a coherent paragraph summarizing the entire video content.

4. Audio Processing and Synchronization:

Speech Recognition: The audio stream is transcribed into text using a speech recognition engine. This process generates a textual representation of the spoken content within the video.
Timestamp Integration: The speech recognition process incorporates timestamps to synchronize the audio-derived text with the corresponding video frames. This allows for later alignment of information extracted from both modalities.

5. LLM-based Mind Map Generation:

Combined Text Input: The combined text description generated from video frames (Prompt 1 output) and the transcribed audio text with timestamps are fed into the LLM once more.
JSON Output: Prompt 2 instructs the LLM to convert the combined textual data into a structured JSON format. This format is chosen for its flexibility and ease of use. JSON allows for efficient representation of hierarchical data, making it suitable for encoding the relationships and connections within the mind map. JSON is a widely recognized and human-readable format, facilitating seamless integration with the mind map visualization tool used by the plugin. The generated JSON file encapsulates the key concepts, themes, and potential relationships identified within the video content. This file serves as the foundation for constructing the visual mind map presented to the user.

6. Visualization the JSON file:

The JSON file containing the structured information is then uploaded to the mind map visualization tool. This tool interprets the data encoded in the JSON file and renders it visually as a mind map. The mind map layout and elements are likely determined by the specific visualization tool used, but will typically represent the key concepts and their relationships as nodes and connecting lines. This visual representation allows users to easily grasp the core content and structure of the video.

3.2 Prompting

3.2.1. Converting Frame-wise Descriptions to Paragraph Description

Prompt 1 (appendix) instructs the LLM to act as a “data expert” and combine the provided dataset (frame descriptions) and transcript into a single, descriptive paragraph. The focus should be on the actual content of the sentences, excluding irrelevant information such as video titles or frame numbers. The prompt emphasizes omitting any redundant or unclear sentences, ensuring only the key information is extracted and integrated into the final output. The result should be a coherent and concise paragraph summarizing the essential content from both sources.

3.2.1. Generating JSON File

Prompt 2 outlines the desired structure and format for generating a JSON file, which will serve as the blueprint for mind map visualization. The JSON should be well-structured, with nodes representing key concepts and edges representing relationships. Each node should have properties like ID, position, size, shape, and label (keyword), while edges should have source, target, label (relationship type), and styles. The JSON should include 20-25 nodes and 20-30 edges, creating a mind map with 1 to 3 levels of branches for hierarchical structure. Visual differentiation using different colors and edge lengths is encouraged to represent relationships clearly and avoid overlapping nodes, focusing on objective interactions and relationships within the video content.

3.3 User interface

3.3.1 Layout

The interface (shown in Figure 8) is divided into two main sections:

1. *Left Pane:* This section displays the video content. Users can likely control video playback using standard video player controls (play, pause, volume, etc.) that are located under the video window.

2. *Right Pane:* This section serves as the mind map workspace. It's where the LLM-generated mind map is visualized and where users can interact with it.

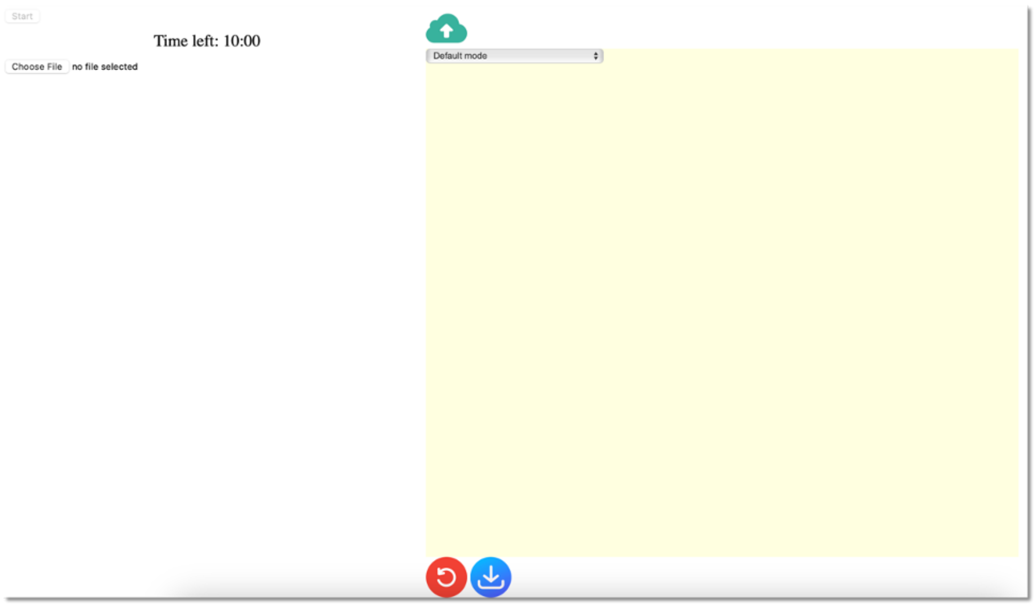


Figure 8: User interface of the mindmap visualising tool. (Source : Author)

The mind map visualization tool offers various functionalities for users to explore and modify the mind map:

1. *Navigation:* In default mode, users can click and drag anywhere on the right pane to pan the mind map around. The mouse scroll wheel allows zooming in and out of the mind map for a closer look or a broader view.

2. *Node and Edge Manipulation:* Nodes (representing key concepts) can be dragged and repositioned within the mind map workspace in the default mode. This intuitive manipulation allows for effortless organization of the mind map structure. Double-clicking a node or edge enables editing its label or title, fostering clear and concise communication of ideas. Right-clicking a node provides options for customizing its appearance (line width, color, thickness) and deleting it. This granular control over visual elements allows users to tailor the mind map's aesthetics to their preferences and enhance readability.

3. *Adding Elements:* A dropdown menu offers options for adding new nodes and edges to the mind map. Selecting "Add Node" allows users to click anywhere on the workspace to create a new node. Selecting "Add Edge" enables users to click on two existing nodes to establish a connection between them, visually representing a relationship. These functionalities empower users to iteratively build upon the LLM-generated mind map, incorporating their own insights and interpretations.

4. *File Management:* The top section of the interface includes a button for uploading a JSON file containing a pre-existing mind map. This enables seamless integration with externally created mind maps. The bottom section contains two buttons: one for downloading the current mind map as a JSON file (for saving or further editing later) and another for refreshing the window, emptying the mindmap pane. This promotes efficient workflow management by allowing users to save their work and clear the workspace for new mind maps.

Overall, the interface is designed for ease of use, allowing users to explore the LLM-generated mind map visually and make basic modifications to suit their needs.

4
Study

Problem Statement | Design | Parameters | Procedure

4.1 Problem Statement

4.1.1 User Experience Map

The literature review has identified significant challenges that designers face during video analysis, particularly in making accurate interpretations. The user experience map illustrated in the FIgure 9 provides a streamlined visualization of the phases involved in video-based design. Each phase, represented by distinct steps, highlights the users' progression through the process and identifies pain points corresponding to each stage. The map also estimates the time and effort required for each task, offering a clear understanding of where improvements can enhance the overall user experience. This visualization serves as a means of empathizing with the designers for whom we are creating this solution.

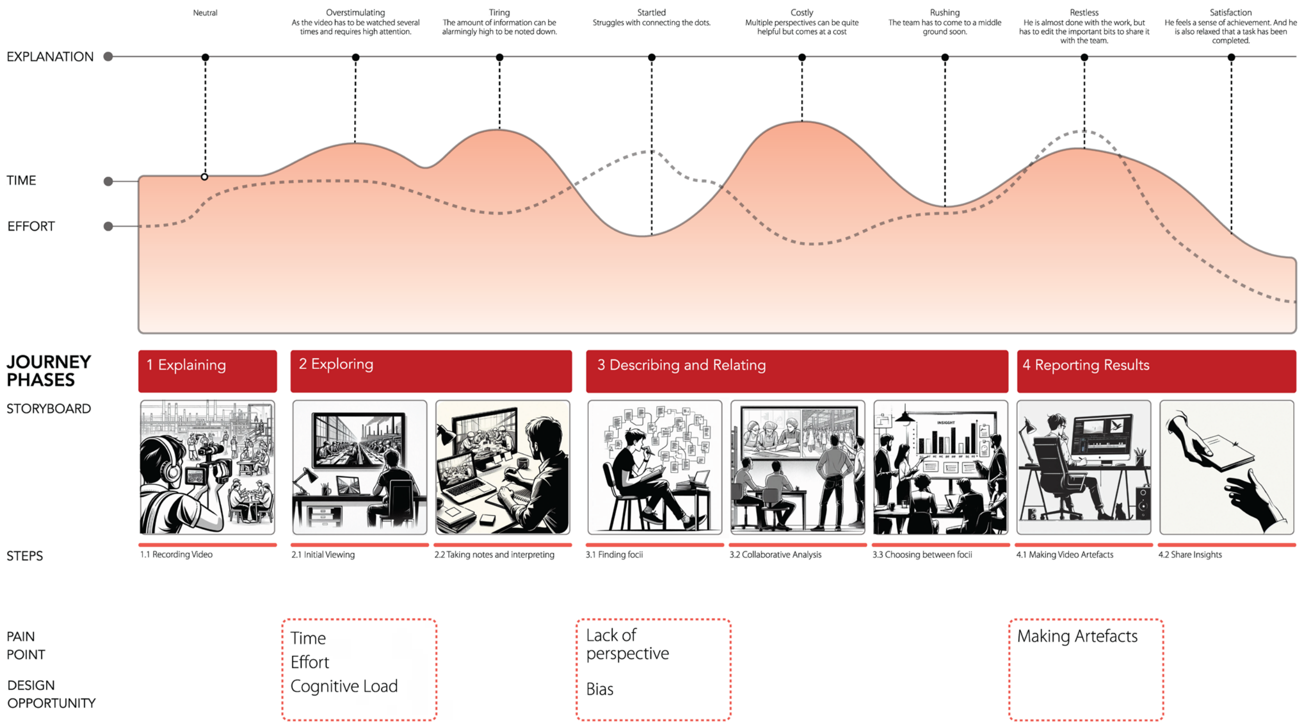


Figure 9: User Experience Map of the designer (Source : Author)

4.1.2 Addressing Pain Points with AI-Generated Mind Maps

To tackle these identified pain points, our tool leverages Large Language Models (LLMs) to generate mind maps from video content. This innovation is expected to bring several key benefits:

1. ***Reduction in Time and Effort:*** Automating the generation of mind maps streamlines the process, significantly reducing the time and effort required in the initial phases of explaining and exploring.
2. ***Alleviation of Cognitive Load:*** By presenting key concepts and their interrelationships visually, the tool helps users quickly grasp the essence of the video content, thus reducing the cognitive load during interpretation.
3. ***Minimization of Bias:*** The tool's capability to generate objective mind maps provides a structured and unbiased overview, which is crucial during the describing and relating phase.
4. ***Simplification of Artefact Creation:*** By organizing insights into structured mind maps, the tool simplifies the creation of video artifacts, making it easier to share comprehensible insights during the reporting phase.

4.2 Study Design

4.2.1 Research Study Objectives

The primary objective of this research study is to evaluate the transformative impact of AI-generated mind maps on the video-based design (VBD) process. This study addresses three critical research questions to provide robust empirical evidence and actionable insights. By conducting a controlled experiment with designers, we aim to explore the comparative benefits and limitations of AI-generated mind maps versus human-generated mind maps.

Rationale for Comparison : Human vs AI

Comparing human and Large Language Models (LLMs) in research studies provides critical insights into the strengths and weaknesses of AI tools, thereby identifying areas for improvement in their development. For instance, studies have shown that while LLMs like GPT-4 exhibit strong planning performance and can effectively use external tools, they still lag behind human performance in complex tasks, highlighting the need for further enhancement in tool-augmented workflows (Li et al., 2023). Additionally, these comparisons help identify the strengths and weaknesses of LLMs in complex tasks, such as crowdsourcing pipelines, where LLMs can simulate some human abilities but still require human oversight for optimal performance (Zhu et al., 2023).

Evaluating LLMs against human benchmarks also provides insights into their cognitive abilities, as seen in adaptive testing frameworks that dynamically adjust question difficulty to better estimate LLM capabilities, revealing that models like GPT-4 can reach the cognitive level of middle-level students (Zhuang et al., 2023). The alignment of AI with human interests and values is another critical area, as LLMs can exhibit unintended behaviors due to their unpredictable learning and adaptation processes, necessitating improved methods for collecting reliable human feedback to train more aligned models (Hagendorff & Fabi, 2022). Finally, the comparison of reasoning errors between humans and LLMs using cognitive psychology tools underscores the importance of developing strategies to induce better performance in LLMs, which are not always responsive to the same prompts as humans (Yax et al., 2024).

Understanding how LLMs and humans differ in generating narrative stories can inform the design of better AI systems, as interleaved human-LLM stories were found to be less preferred than those generated solely by LLMs, indicating areas for improvement in AI-generated content (Zhao et al., 2023). Overall, comparing human and LLM performance in research could enrich our understanding of LLM cognition and collaborative potential.

Figure 10: Hybrid Intelligence Art (Courtesy : Is It Really A Battle of the Brains? AI Versus Human Intelligence, 2024)

4.2.2 Research Questions

RQ 1. How do AI-generated mind maps compare to human-generated mind maps in terms of efficiency and effectiveness in aiding video-based design (VBD)?

The integration of AI into the design process is an emerging area of interest, yet there is limited research on how AI-generated mind maps specifically impact VBD workflows compared to traditional human-generated mind maps. The literature on VBD highlights the importance of efficiently synthesizing large volumes of video data to extract meaningful insights (Ylirisku & Buur, 2007). Studies have shown that AI can potentially speed up this process by quickly generating mind maps from video data (Ma et al., 2016; Yang et al., 2016). However, the effectiveness of these AI-generated mind maps in accurately capturing nuanced user interactions and contextual details remains underexplored. Existing research suggests that human-generated mind maps, while potentially more time-consuming, can be more effective in capturing complex, context-specific information due to the human ability to interpret subtle cues and contextual nuances (Palaniappan et al., 2023). Understanding how AI-generated mind maps compare to human-generated ones in terms of efficiency and effectiveness can help determine the best practices for incorporating AI into VBD. This research question addresses the gap in knowledge regarding the comparative benefits and limitations of AI in design analysis, aiming to optimize the VBD workflow for better efficiency without compromising on the depth of insights.

RQ 2. What impact do AI-generated mind maps have on the designer's cognitive load, enjoyment, and perceived usefulness compared to human-generated mind maps in aiding VBD?

Cognitive load, enjoyment, and perceived usefulness are critical factors influencing the adoption and effectiveness of new tools in the design process. The literature on VBD and user-centered design emphasizes the importance of tools that not only enhance productivity but also support designers' cognitive and emotional well-being (Ma et al., 2016). High cognitive load can hinder the design process by overwhelming designers and reducing their ability to think creatively and make informed decisions (Ylirisku & Buur, 2007). Research on AI tools in other domains has shown mixed results, with some studies indicating that AI can reduce cognitive load by automating routine tasks while others suggest it can increase cognitive load due to complexity and the need for constant human oversight (Vasconcelos et al., 2023). Enjoyment and perceived usefulness are key factors in technology acceptance models (Khechine et al., 2016). Tools that are enjoyable to use and perceived as useful are more likely to be adopted and effectively integrated into the design process (Khechine et al., 2016). This research question aims to explore the balance between the cognitive demands of using AI-generated mind maps and their potential benefits in terms of enjoyment and perceived usefulness. Addressing this gap will provide insights into how AI tools can be designed and implemented to support designers' cognitive processes and enhance their overall experience, ultimately leading to more effective VBD workflows.

RQ 3. What factors influence the effectiveness of AI-generated mind maps in aiding designers' decision-making processes?

Identifying the factors that influence the effectiveness of AI-generated mind maps is crucial for optimizing these tools and ensuring they support designers' decision-making processes effectively. The literature on VBD highlights various challenges, such as data overload and the need for critical interpretation, that can impact decision-making. VBD involves dealing with large volumes of video data, which can be overwhelming and difficult to manage without effective tools (Ylirisku & Buur, 2007). AI-generated mind maps might have the potential to streamline this process, but their effectiveness might depend on various factors, such as the quality of the AI algorithms, the relevance and clarity of the generated maps, and the designers' ability to interact with and interpret these maps. Factors such as the context of use, the specific tasks involved, and the individual differences among designers (e.g., experience level, familiarity with AI tools) could also play significant roles in determining the effectiveness of AI-generated mind maps in designing. Understanding these factors will help in developing guidelines for the use of AI tools in design and improving their design to better support the VBD process. This research question addresses the need for a deeper understanding of how AI tools can be tailored to fit the specific needs and contexts of designers, ultimately enhancing their decision-making capabilities and the overall quality of design outcomes.

4.2.3 Chosen Contexts for the Study

To assess the effectiveness of the mind map tool on various types of content, we opted for two video scenarios, each lasting 2 minutes and 20 seconds. Additionally, using different contexts allowed the study to determine if the context influenced the effectiveness of mind mapping. These scenarios were carefully chosen to represent the two primary categories of video content that designers deal with: 1) repetitive videos and highly informative videos such as CCTV, Point Of View footage, and 2) user-product interactions.

The chosen contexts are:

1. Autonomous Car Navigation:
This video showcases an autonomous car taxi navigating through a complex urban intersection with traffic signals and pedestrians. It provides insights into the car's navigation system, interaction with other vehicles, and pedestrian safety measures. This context is relevant to designers working on interfaces for autonomous vehicles or transportation apps. A screenshot of the video is shown in Figure 11 below.

2. Using iPhone Accessibility Features:
This video features a blind woman demonstrating how she utilizes accessibility features on her iPhone, such as voiceover and screen reader, to perform daily tasks. The video highlights navigating the web, typing, and posting a tweet. This context is valuable for designers focusing on inclusive user interfaces and ensuring accessibility for users with visual impairments. A screenshot of the video clip is shown in Figure 12 below.

By selecting these contrasting video topics, we aimed to assess the mind map tool's ability to handle different information types and its potential benefits for various design needs while maintaining consistency in video length to ensure fairness in participant evaluation. To ensure a fair comparison, both videos were standardized to the same bit rate.

Figure 11: Autonomous Car driving in a busy street. (Courtesy : Kevin Chen, 2023)

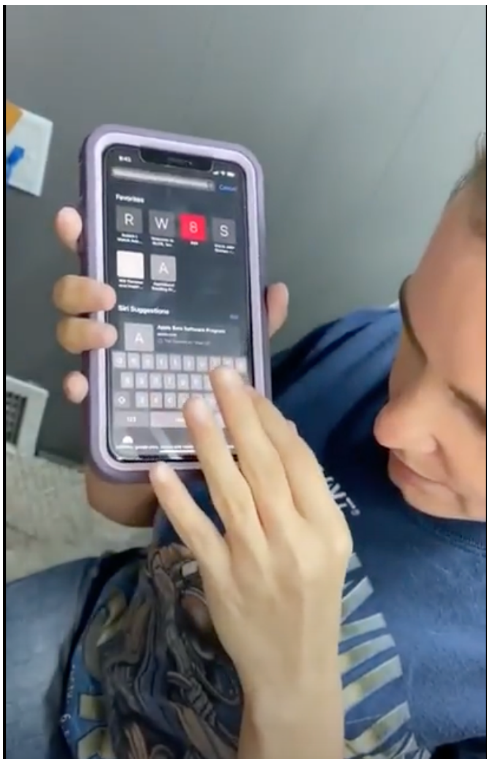
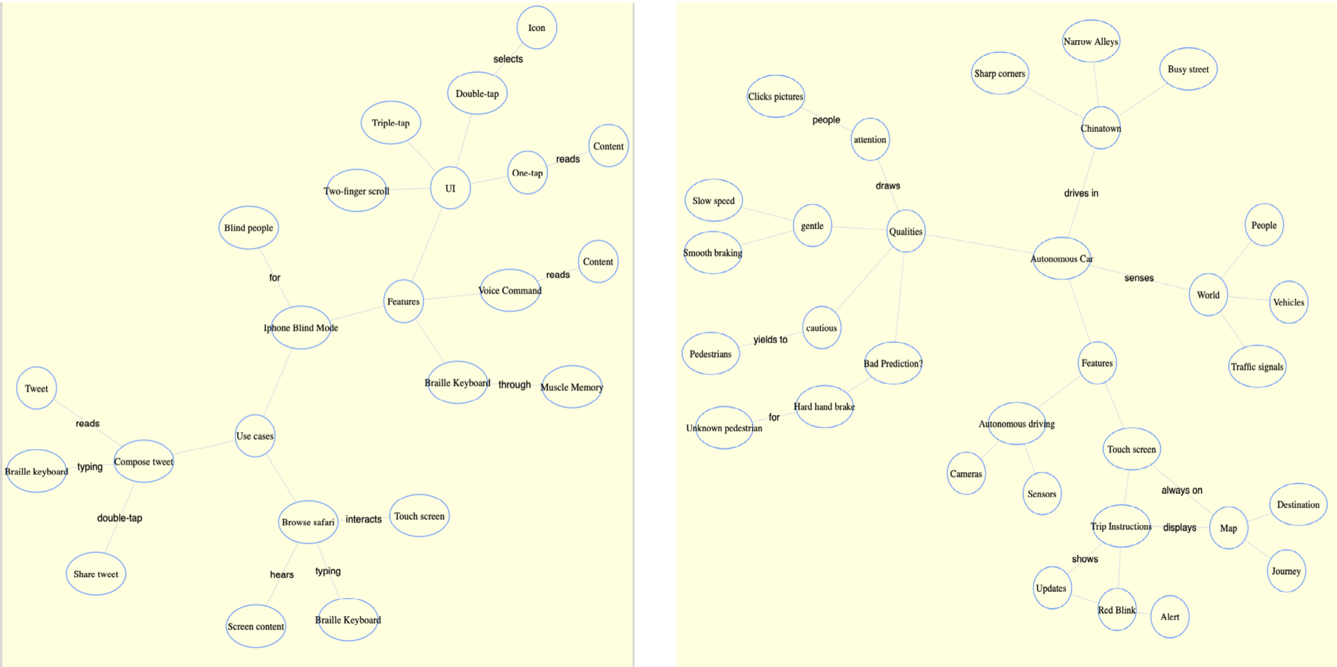


Figure 12: Blind woman interacting with her phone. (Courtesy : Storyful News & Weather, 2020)

4.2.4 Baseline Condition for Human-Generated Mind maps

To ensure consistency in the mind map creation process, I (a designer with 3 years of experience) took the lead in developing mind maps for both videos. I invested 10 minutes in analysing each video twice, emphasizing the comprehension of the central idea and fundamental concepts instead of delving into excessive details. Following that, I hand-drew a radial mind map on paper, as this method is widely used in mind mapping to help organize thoughts around a central theme. Subsequently, I invested an extra 20 minutes in digitally transferring the mind map into a mind mapping tool without incorporating colours to uphold simplicity. This standardized method served as a foundation for comparing the AI-generated mind maps. The mind maps created by the human designer is shown below in Figure 13.



(a) Context of Blind woman using her phone

(b) Context of Autonomous Car

Figure 13: The mindmaps created by the human designer (Source : Author)

4.2.5 Apparatus

The experiment was conducted in a typical office environment to simulate a realistic design workflow. Participants used a desktop computer configured to run the LLM mind map generation tool as a localhost application. Standard office equipment was provided, including a keyboard, mouse, and speakers. To assess visual attention during mind map creation, participants wore eye-tracking glasses (Pupil Labs NEON with a 200 Hz sampling rate). These glasses connected to a dedicated Android phone via a USB-C cable to record eye-movement data. The data included eye gaze trajectories, fixation positions, and blink patterns. Additionally, the camera captured the whole study and the interview sessions conducted after the experiment. AprilTags are widely utilized in computer vision applications for robust object detection and tracking due to their computational efficiency and ease of use with monocular cameras (AprilTag, n.d.). Therefore, four AprilTags, which are were affixed to each corner of the computer screen to enable the glasses to accurately identify the viewing area. The setup of the study is shown in Figure 14.

(a) Participant viewing the video during study

(b) Participant analysing the mindmap during study

Figure 14: Pictures showing the experimental set-up (Source: Author)

4.2.6 Participants

We recruit 28 design graduates from the Industrial engineering faculty at Delft university of technology following approval from the ethics board and ensuring none had cognitive disorders. All participants were informed about and agreed to the consent form before the experiment commenced. We collect participants' age, self-rated design experience, educational level, current level of trust and reliance on AI tools in design process, and self-rated experience in VBD. Before commencing the experiment, participants will be provided with an informed consent form to review and sign. The consent form will detail the study procedures, potential risks and benefits, and participants' rights.

Different groups started with different tasks and contexts, controlling for potential learning effects. If participants always began with human-generated mind maps, they might become more efficient or knowledgeable over time, skewing the results. Counterbalancing the study ensured that any learning or fatigue effects were evenly distributed across all conditions. This approach also ensured a fair comparison between human and LLM-generated mind maps. By having participants switch between the two methods, the study could more accurately compare their effectiveness, controlling for individual differences and providing a clearer picture of the relative advantages and disadvantages of each method. Subsequently, all participants interacted with both types of mind maps. This approach ensured that any observed differences in user experience or performance stemmed from the mind map type itself, rather than the order of presentation. The distribution of participants among different groups and their familiarity with video based design activities is shown in Figure 15 and 16 respectively.

	Task Number 1		Task Number 2		
Group	**Who made the Mindmap**	**Context**	**Who made the Mindmap**	**Context**	**Number of Participants**
A	Human	Car	LLM	Phone	7
B	LLM	Phone	Human	Car	7
C	LLM	Car	Human	Phone	7
D	Human	Phone	LLM	Car	7

Figure 15: Table shows the distribution of participants within various groups

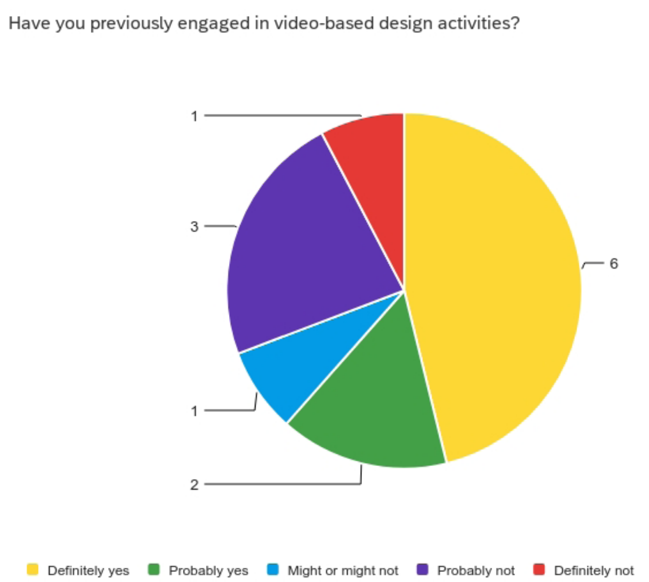


Figure 16: Table shows the familiarity of participants in VBD tasks

4.3 Evaluation Parameters

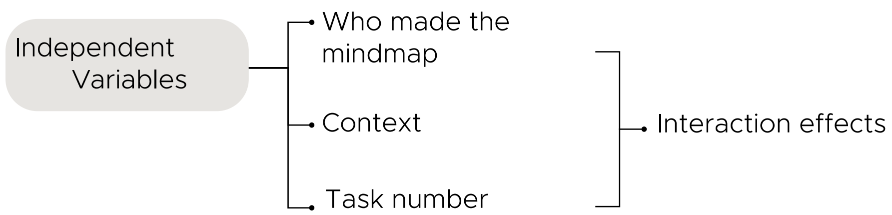
4.3.1 Independent Variables

In the study, the independent variables are the factors that were manipulated to observe their effects on the dependent variables. The key independent variables in this study include:

1. ***Who Made the Mind Map:*** This variable was included to compare the effectiveness, efficiency, and user perception between mind maps created by humans and those generated by a language model (LLM).
   Levels: Human-generated vs. LLM-generated mind maps.

2. ***Context:*** To evaluate whether the context in which the mind map is used influences its effectiveness and usability.
   Levels: Autonomous Car vs iPhone for Blind people

3. ***Task Number:*** To assess whether the order or sequence of tasks impacts the effectiveness and efficiency of mind mapping, and to control for potential learning or fatigue effects over time.
   Levels: Task number 1 vs Task number 2



These independent variables were carefully chosen to explore various dimensions of mind mapping in a detailed and controlled manner, ensuring that the study could provide comprehensive insights into the relative benefits and drawbacks of human vs. LLM-generated mind maps across different contexts and tasks.

4.3.2 Dependent Variables

The study utilizes a variety of dependent variables to measure the impact and effectiveness of human-generated versus AI-generated mind maps. These variables capture different dimensions of user interaction, cognitive load, usability, and overall user experience.

Mindmap Rubric

A pre-defined scoring system assesses the mind maps on various criteria, including accuracy, completeness, structure, and relevance to visual-based design (VBD) tasks. The holistic approach captures the nuanced and integrative aspects of a mind map's knowledge representation (Hua & Wind, 2018). This method is advantageous because it allows for a more comprehensive evaluation of the mind map generated as seen in our literature review. The holistic method described was detailed such that more guidance was given to the marker scoring the mind map on a scale of 1-100. (appendix). The criteria below were used in assessing each mind map.

1) ***Identification of triggers in the problem:*** the degree to which the student is able to identify the key concepts in the problem.
2) ***Development of valid concept links:*** the ability of the students to explore their knowledge by developing concepts further.
3) ***Development of hierarchies:*** the arrangement of concepts in a logical manner with the more fundamental concepts at the centre and more specific as concepts on the periphery of the map.
4) ***Identification of cross links and relationship links:*** the ability to show the meaningful connections between different concepts (cross links) and links within a concept (relationship link).

Edited Mindmaps

Efficiency is measured through task durations for editing and analyzing mind maps. This study aims to identify significant differences in task durations based on who made the mind map (human vs. AI) across different contexts. Quantitative measures, such as the number of nodes and edges added or deleted, provide insight into the complexity and thoroughness of the edits made to each mind map.

The qualitative analysis includes the content of nodes and words added in each mind map. These metrics help quantify the amount of information captured and the level of detail provided in each mind map, offering a straightforward comparison between human-generated and AI-generated mind maps.

NASA TLX

The NASA Task Load Index (NASA-TLX) measures subjective workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration level (NASA-TLX Web App, 2020). This multidimensional tool identifies specific workload sources, aiding targeted design improvements (Cao et al., 2009). It helps reveal inefficiencies in AI system interactions, promoting better interface designs (Mozannar et al., 2022). NASA-TLX's simplicity and detailed diagnostic capabilities make it a popular choice for workload assessment in various domains, including human factors and usability testing (McKendrick & Cherry, 2018). The tool's comprehensive nature provides valuable insights for enhancing AI system performance (Cao et al., 2009).

The NASA Task Load Index (NASA-TLX) is used to assess the subjective workload experienced by participants. This multidimensional tool measures six dimensions:

1. *Mental Demand:* Assesses the mental and cognitive effort required to perform the task. This includes the complexity and concentration needed.
2. *Physical Demand:* Evaluates the physical effort required to complete the task, such as movement, dexterity, and strength.
3. *Temporal Demand:* Measures the time pressure felt by participants while performing the task. This reflects how hurried or rushed the participants felt.
4. *Performance:* Gauges the participants' perception of their success in completing the task. This includes how well they think they performed and their satisfaction with the results.
5. *Effort:* Assesses the overall amount of effort participants had to exert to complete the task, combining mental and physical aspects.
6. *Frustration Level:* Measures the participants' feelings of stress, annoyance, and irritation experienced during the task.

The study collects data on participants' perceived workload after interacting with human-generated and AI-generated mind maps. The participants could choose from a scale of 1-100, with each increment after 5 points, therefore, a total of 20 options to choose from.

Semi-Structured Interview

Semi-structured interviews provide deeper insights into participants' experiences and perspectives. Participants are asked for general feedback on the mind map tool, specific features they found useful or challenging, and suggestions for improvement. They are also asked to guess which mind map was generated by AI and which was created by a human, followed by a discussion on the features that influenced their decision. Additionally, participants are queried about their preference for one type of mind map over the other based on clarity, creativity, and overall effectiveness in conveying information. Finally, participants are asked about possible applications of the mind map generator in educational settings, collaborative projects, or professional environments. This qualitative data complements the quantitative measures and provides a richer understanding of user experiences and perceptions (Kvale, 2008).

UTAUT 2

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model enhances the original UTAUT framework by including factors like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit to better understand user behavior and technology adoption, especially in AI contexts (Khechine et al., 2016). Performance expectancy, or the perceived benefits of using the AI system, is a significant predictor of user behavior (Zhang, 2020; Kułak et al., 2019). Effort expectancy, the ease of use, is crucial in shaping user intentions, particularly for AI-integrated systems (De Blanes Sebastián et al., 2022; Chatterjee et al., 2021). Social influence and facilitating conditions also play essential roles, though the latter shows mixed results depending on context (Awanto et al., 2020). Factors such as trust, personal innovativeness, and perceived privacy risk are critical for AI adoption, emphasizing user-centric design and privacy (De Blanes Sebastián et al., 2022).

The UTAUT2 model extends the original UTAUT framework to better understand user behavior and technology adoption, particularly in the context of AI systems. Variables include:

Performance Expectancy: Perceived benefits of using the AI system
Effort Expectancy: Ease of use, which significantly impacts user acceptance and adoption
Social Influence: Impact of others' opinions on the user's decision to adopt the technology, crucial in educational and organizational settings (Khechine et al., 2016).
Facilitating Conditions: Availability of resources and support, which influence actual usage behavior
Behavioral Intention: Intent to use the technology
Hedonic Motivation: Fun or pleasure derived from using the technology
Price Value: Cost-effectiveness of the technology
Habit: Routine use of the technology (Venkatesh et al., 2012).

The study aims to understand how these factors influence participants' willingness to adopt and use the mind map tool in their design work (Venkatesh et al., 2012). A detailed list of questions can be found in the appendix. Each variable was split into several questions accordingly, and participants were asked to rate them on a scale of 1 to 5, with 1 meaning strongly disagree, 5 meaning strongly agree, and 3 being neutral. An expanded list of all questions can be found in the appendix.

Eye Tracking Glasses

Using eye-tracking glasses in user-centered design research offers critical insights into user behavior and cognitive processes. This technology measures user attention and information processing, which is essential for optimizing designs (Alrefaei et al., 2023). Eye tracking reveals friction points that may go unnoticed, identifies user interaction patterns, and supports remote studies (Jung et al., 2021; Stone & Chapman, 2023). Metrics like heat maps and fixation points help improve interface design by aligning with user habits and preferences (Agustianto et al., 2022). It also evaluates user emotions and satisfaction, providing objective measures to enhance UX design (Jian et al., 2022; Wu, 2022).

Eye-tracking technology measures where participants focus their attention and how they process information while interacting with the mind maps. Metrics include:

1. ***Heat Maps:*** Visual representations of areas of interest (Holmqvist et al., 2011).
2. ***Saccades:*** Rapid eye movements between points of fixation, indicating how users scan the information (Rayner, 1998).
3. ***Fixations:*** Periods where the gaze is held steady, reflecting areas of high cognitive processing (Duchowski, 2007).
4. ***Pupil Sizes:*** Indicative of cognitive load (Beatty, 1982).
5. ***Blinks:*** Can indicate cognitive processes and fatigue (Stern et al., 1994).

These metrics provide detailed insights into user behavior and cognitive processes, helping identify areas of interest and potential friction points in the user interface (Poole & Ball, 2006; Holmqvist et al., 2011).

4.4 Procedure

4.4.1 Preparation

Participants were individually invited to the COALA room in the Applied Labs at their scheduled times. Upon arrival, they were provided with an informed consent form and a brief demographics questionnaire. After completing these documents and receiving a de-identified participant ID, researchers explained the experiment's purpose and procedures. Visual acuity was then assessed to ensure compatibility with the eye-tracking glasses. Finally, participants were guided to their designated positions in front of the computer monitor.

4.4.2 Main Session

Following preparation, participants received a briefing on the video context and their design task role. They were then fitted with eye-tracking glasses and shown a tutorial video demonstrating navigation within the LLM mind map generation tool. Timestamps were recorded at the start and end of each task.
The main session consisted of two rounds. In each round, participants watched a two-minute video related to video design. They were then presented with a human-generated mind map summarizing the video content. Participants were notified to pay close attention to the user's behavior, interactions and decision-making processes and think out loud as they watch through the video. The users are asked to think aloud during their interaction with the product to allow the researchers to capture their thoughts in addition to their actions. The test is documented in detail with tools such as data forms and video (Ylirisku & Buur, 2007). The participants were asked to only watch it once, with no pausing or rewinding. Later, participants were asked to carefully review and evaluate the mind map using a pre-defined mind map assessment rubric. This rubric provided space for written justifications for their ratings. Next, participants were given time to modify the existing mind map to better represent the video and improve its usability for documentation purposes.

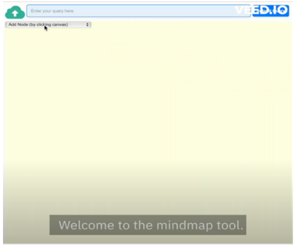
Upon completing the main task for a particular video and mind map combination, participants assessed their workload using the NASA-TLX scale and provided feedback on their overall experience by completing the UTAUT2 survey. Each round of the main session (video viewing, mind map evaluation and modification, workload assessment, and survey completion) took approximately 20 minutes.

4.4.2 Post Session

After completing both rounds, participants were invited to share their overall experience, raise any concerns, and answer questions regarding the study. They were then asked to guess which mind map (human-generated or LLM-generated) they believed originated from each video. A follow-up discussion explored the reasoning behind their guesses and the perceived characteristics of human-made versus AI-generated mind maps. Finally, participants identified potential applications for the LLM tool and were thanked for their contribution. They were then compensated with a gift card, and the entire study concluded in approximately 50 minutes.

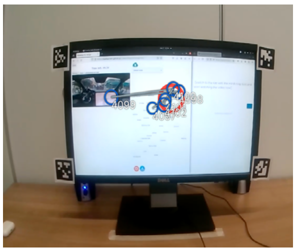
Beginning of the Study

Step 1 Tutorial Video

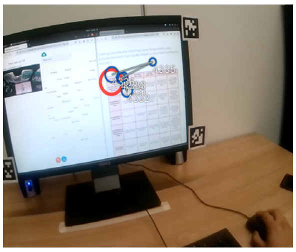


Step 2 Watch Video

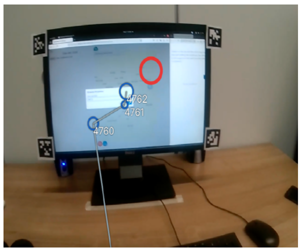
Step 3 View and Analyse the mind map



Step 4 Rate the mind map using the mind map rubric

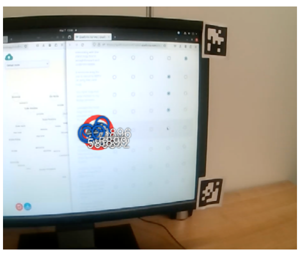


Step 5 Make edits/ changes to the mind map



Step 6 Answer NASA-TLX questionnaire

Step 7 Answer UTAUT 2 questionnaire



Repeat the following steps for Context 2

End of the Study

5

Results

Analysis | Research Questions | Insights

Chapter Overview

In this chapter, we delve into the complex process of data analysis and present the compelling results from our study on the impact of LLM-generated mind maps in video-based design. We begin by identifying the optimal analytical methods for processing the data, a crucial step that involved evaluating various techniques to handle the statistical data collected from our 28 participants.

The combination of quantitative measures and qualitative insights provided a holistic view of the data, which is crucial for answering our research questions effectively. Our analysis starts with the meticulous selection of these methods, ensuring they align with the study's objectives. This step is followed by detailed procedures on how the analysis was performed.

Next, the results section unfolds with a clear narrative addressing each research question. We first explore how AI-generated mind maps compare to human-generated ones in aiding video-based design, focusing on efficiency and effectiveness. The analysis reveals significant time savings and reduced analytical rigor with AI-generated mind maps. Next, we assess the impact on designers' cognitive load, enjoyment, and perceived usefulness, highlighting the positive reception and enhanced user experience with AI-generated tools. We then delve into the factors influencing the effectiveness of AI-generated mind maps in designers' decision-making processes, offering deeper insights into the variables at play.

For each research question, we provide a succinct summary of the findings, enriched with quantitative results and qualitative narratives. This structured approach ensures that the answers are clear and supported by robust data. Moving beyond the immediate results, we discuss higher-level insights such as the drawbacks and limitations of AI-generated mind maps. We reexamine our initial hypotheses in light of the findings, noting which were validated and which require further reflection. Additionally, we explore how the context of the videos and the number of tasks influenced the outcomes, offering nuanced perspectives on the conditions that enhance the benefits of AI-generated mind maps. The image below (Figure 17) illustrates the process by which different methods and tools from our study were utilized to derive key parameters for answering our research questions. This visual representation highlights the interconnections between the various elements of our study and how they contributed to our overall findings.

Finally, the results chapter synthesizes these findings to support practical implications for future design processes and tool development in the future. While the main text focuses on significant results and actionable insights, detailed data and additional results are provided in the appendix for thorough reference. This coherent narrative not only presents the findings but also connects them to the literature and practical applications, making the chapter both coherent and engaging.

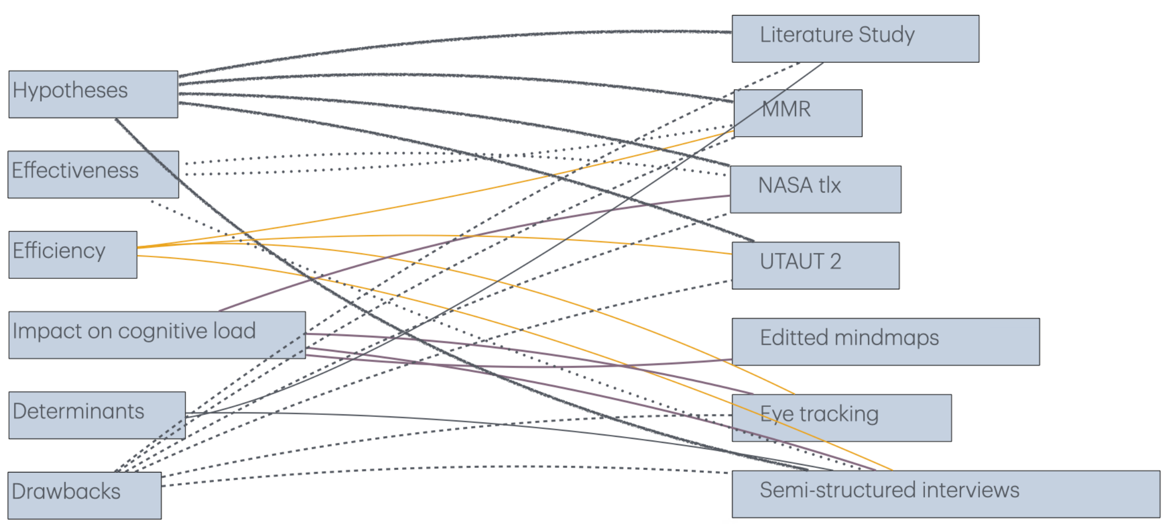


Figure 17: Fuzzy end of the data analysis (Source: Author)

5.1 Data Analysis

5.1.1 Quantitative Analysis

Mixed model analysis, also known as hierarchical linear modeling (HLM) or multilevel modeling, is a statistical technique used to analyze data that have a complex structure, such as repeated measures, nested data, or data with random effects (Muradoglu et al., 2023). This method is particularly useful when the data points are not independent of each other, such as in longitudinal studies or studies with clustered data (Shi et al., 2020). Mixed-effects models are much better suited for our study. These models can handle the fact that participants are exposed to different combinations of mindmap creators and contexts. They incorporate both fixed effects for the main factors and random effects to account for variability between participants, making them suitable for our study.

Methodology

In our study, a mixed model analysis was used to investigate the effect of different conditions on the quantitative data obtained from the study. The key components of the mixed model analysis include fixed effects, random effects, repeated measures, and covariance structure.

Application	Recommended test	Feasibility
Fixed Effects	Who_made_the_mindmap Context Task number Interaction effects	Fixed effects are the systematic effects that we are interested in estimating.
Random Effects	Participant ID	Random effects account for the variability due to the subjects (participants) in the study.
Repeated Measures	Who_made_the_mindmap Context	Repeated measures refer to the multiple observations taken from the same subjects
Covariance Structure	Autoregressive Covariance	This structure assumes that the correlations between repeated measures decrease as the time interval between them increases.

5.1.2 Qualitative Analysis

For the qualitative analysis, thematic analysis was performed using ATLAS.ti to delve deeply into the participants' experiences and perceptions. Thematic analysis is a method for identifying, analyzing, and reporting patterns (themes) within data, organizing and describing the data set in rich detail (Ayre, 2022). Initially, the transcripts of the interviews were reviewed, marking significant quotes that captured important insights. These quotes were then grouped under specific codes, facilitating the organization and categorization of the qualitative data. By systematically coding the data, key themes that emerged from the participants' responses were identified, providing a comprehensive understanding of the overarching feedback and common issues raised. In addition to the thematic analysis, heatmap analysis of the edited mind maps across all four cases was conducted. This involved creating visual representations to observe how the distribution of concepts and connections changed after editing. The heatmaps highlighted areas of high activity (hotspots) and low activity (weak spots), revealing key changes made to the mind maps. Analysis also focused on which words and terms were frequently deleted, missing, or relocated, offering insights into the editing behaviors and the elements participants found most and least valuable.

5.2 Answering Research Questions

(RQ.1) "How do AI-generated mind maps compare to human-generated mind maps in terms of efficiency in aiding video-based design (VBD)?"

To address the first research question, we utilized various measures to assess efficiency. These measures included edit task duration, analysis task duration, temporal demand, and qualitative insights from participant interviews. Below, we present and analyze these results, grouping them to support a coherent narrative and providing a comprehensive answer to the research question.

Quantitative Results

Edit Task Duration : The time taken to edit the mind maps was one of the primary measures used to assess efficiency. For AI-generated mind maps, the mean edit duration was 443.51 seconds (SE = 36.39), whereas for human-generated mind maps, the mean edit duration was 328.37 seconds (SE = 36.39). This indicates that AI-generated mind maps took, on average, 115.14 seconds longer to edit than human-generated ones, as seen in Figure 18.
A mixed model analysis revealed a significant effect of the mind map creator on edit task duration, $F(1, 71.12) = 5.64$, $p = .020$, suggesting that AI-generated mind maps required significantly more time to edit compared to human-generated mind maps. Additionally, the average time to complete task 1 was 445.144 seconds, while the average time to complete task 2 was 326.737 seconds. Also, the task number effect was significant, $F(1, 51.18) = 6.04$, $p = .017$, indicating that task durations decreased with successive tasks, likely due to participants' workflow becoming more efficient with practice. However, the interaction effects were not significant, implying that other factors did not significantly influence the edit duration.

Analyse Task Duration : The time taken to analyze the mind maps was another measure of efficiency. For AI-generated mind maps, the mean analysis duration was 128.09 seconds (SE = 12.26), whereas for human-generated mind maps, the mean analysis duration was 104.17 seconds (SE = 12.26). AI-generated mind maps took, on average, 23.92 seconds longer to analyze than human-generated mind maps, as seen in Figure 18.

However, a mixed model analysis indicated no significant effect of the mind map creator on analysis task duration, $F(1, 52.34) = 2.13$, $p = .152$, suggesting that the source of the mind map (AI vs. human) did not significantly impact the time taken to analyze the maps. Context and task number also did not have significant effects.

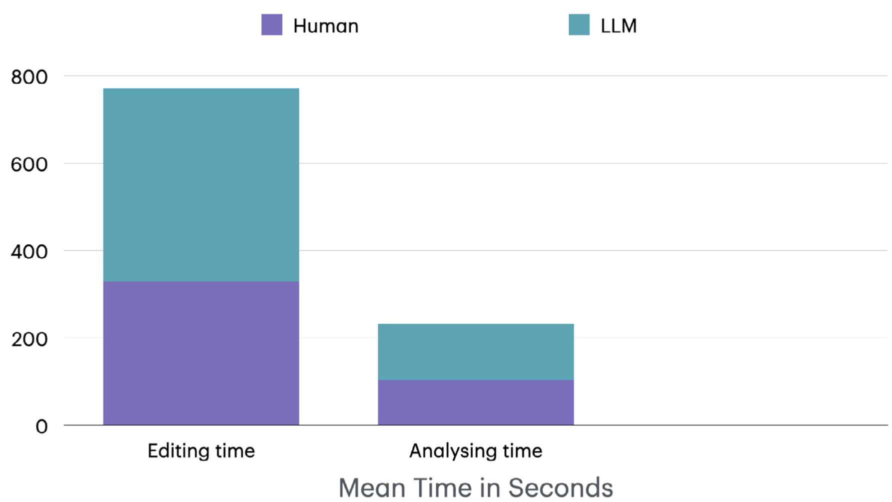


Figure 18: Bar Chart of Mean Durations compare by Human vs LLM (Source: Author)

Temporal Demand : Temporal demand, measured through NASA TLx, was assessed based on participants' ratings of time pressure experienced during tasks. The estimated marginal means indicated that participants rated the temporal demand higher for AI-generated mind maps ($M = 50.71$, $SE = 4.92$) compared to human-generated mind maps ($M = 40.71$, $SE = 4.92$). This suggests participants experienced more time pressure with editing the AI-generated mind maps.

A mixed model analysis revealed a non-significant effect of the mind map creator on temporal demand, $F(1, 23.65) = 3.92$, $p = .059$, indicating no statistically significant difference in perceived temporal demand between AI-generated and human-generated mind maps, although there was a trend towards higher temporal demand for AI-generated maps. The task number had a significant effect on temporal demand, $F(1, 23.65) = 5.45$, $p = .028$, with higher temporal demand reported for task number 1 ($M = 51.61$, $SE = 4.92$) compared to task number 2 ($M = 39.82$, $SE = 4.92$). This suggests that temporal demand decreased with successive tasks, likely due to participants' workflow becoming more efficient with practice. However, the interaction effects were not significant.

Qualitative Results

Qualitative feedback from participant interviews further illuminated the efficiency aspects of AI-generated versus human-generated mind maps. Traditional note-taking is inherently more time-consuming as it requires designers to manually observe, interpret, and record information from the video. This process can be labor-intensive and prone to human error. Participant C1 mentioned, "Like analyzing video can be tires and burns, and then take a lot of time."

Without the automated structure provided by AI, traditional note-taking demands greater cognitive effort from the user. This can slow down the process as designers spend more time categorizing and organizing their notes. In contrast, AI-generated mind maps significantly enhance efficiency by automating the initial stages of data capture and organization. Participant D6 highlighted the time-saving aspect: "You just click one click and you get this mind map, it's insanely valuable because you don't do much and if it gets a bit better and a bit more structure and focused like on just basic things not so much analysis." Participant A2 stated, "It capture all the things and if I don't want it, I can just discard it if I don't like, takes me much less time and I feel like it's way more efficient." This reflects the reduced need for manual note-taking and the advantages in the ability to quickly discard irrelevant information.

Summary

In summary, while AI-generated mind maps took longer to edit and analyze than human-generated mind maps, they significantly reduced the need for manual note-taking and allowed designers to quickly discard irrelevant information. The qualitative feedback indicated a strong preference for the efficiency and convenience offered by AI-generated mind maps, despite the slightly higher temporal demand. Overall, AI-generated mind maps show promise in aiding video-based design by streamlining the process and freeing up valuable time for designers to focus on more creative and analytical aspects of their work.

(RQ.2) *"How do AI-generated mind maps compare to human-generated mind maps in terms of effectiveness in aiding video-based design (VBD)?"*

To address the second research question, we examined several key measures: mind map rubric scores, NASA TLX scores, UTAUT2 Performance Expectancy, the number of nodes added, and qualitative feedback from participant interviews.

Quantitative Results

Mind Map Rubric :

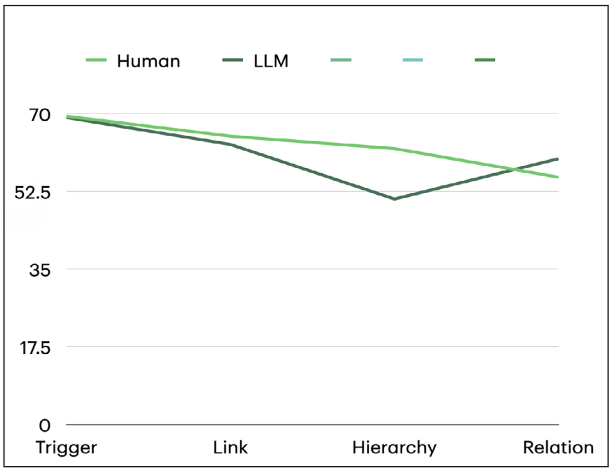


Figure 19: Bar Chart of Mean MMR Scores (Source: Author)

The effectiveness of AI-generated mind maps compared to human-generated mind maps was analyzed across four categories: Triggers, Relation Links, Cross Links, and Hierarchy. The results from the mixed model analysis revealed the following significance values:

Triggers: $F(1,24.695) = 0.009$, $p = .927$
Relation Links: $F(1,24.967) = 0.776$, $p = .387$
Cross Links: $F(1,24.002) = 0.242$, $p = .627$
Hierarchy: $F(1,24.787) = 7.257$, $p = .012$

A non-significant difference was found between AI-generated and human-generated mind maps for Triggers, Relation Links, and Cross Links categories, indicating comparable effectiveness in these areas. However, a significant difference was found in the Hierarchy category, with human-generated mind maps outperforming AI-generated mind maps, suggesting better organization of hierarchical information. Figure 19 shows a significant gap in the values of Human vs LLM Mean scores for hierarchy. The estimated marginal means for Hierarchy were $M = 62.14$ ($SE = 4.37$) for human-generated maps and $M = 50.79$ ($SE = 4.37$) for AI-generated maps. This superior performance by human-made mind maps in organizing hierarchical information may be attributed to humans' ability to structure and categorize complex relationships more efficiently.

NASA TLX Performance :

The NASA TLX scores were used to measure perceived workload and task performance. The mean TLX performance for human-made mind maps was $M = 53.32$ ($SE = 4.03$) while for AI-generated mind maps it was $M = 51.04$ ($SE = 4.03$). The effect of who made the mind map on TLX performance was not statistically significant ($F(1, 23.587) = 0.605$, $p = 0.444$). This indicates that participants' perceived workload and task performance were similar for both AI-generated and human-generated mind maps.

However, the context had a significant effect on TLX performance ($F(1, 23.587) = 7.812$, $p = 0.010$). This highlights that the situational context in which the mind maps are used plays a more crucial role in determining their effectiveness than whether the mind maps were created by AI or humans.

Number of Nodes added : In terms of the number of nodes added to the mind maps, human-generated maps had more nodes added (M = 5.36, SE = 1.03) compared to AI-generated maps (M = 2.79, SE = 1.03). There was a significant effect of who made the mind map on the number of nodes added, $F(1, 24.655) = 4.398$, $p = .046$. Neither context ($p = .423$) nor task number ($p = .528$) had a significant effect on the number of nodes added.

Qualitative Results

Heatmaps :

The heatmap analysis in our study examines the frequency and significance of nodes in mindmaps created by humans and language models (LLMs) across two contexts: autonomous cars and blind individuals using phones. The heatmaps (shown in Figure 20 and 21) visually represent node occurrences, with darker colors indicating higher frequency and central importance, while lighter colors show nodes that were often removed.

The results reveal that both human-made and LLM-made mindmaps effectively highlight central themes. In the human-generated mindmaps, nodes are more structured and grouped, providing a clear and organized layout. Conversely, LLM-generated mindmaps have more nodes directly attached to the central node, indicating a different organizational style. Participants frequently removed nodes directly connected to the central node in LLM mindmaps, suggesting a need to restructure and simplify these maps for better clarity. The most deleted nodes were typically redundant or added no significant information, showing participants' preference for concise and relevant data.

In the context of autonomous cars, the hotspots included terms like "driverless car," "safety," "city street," and "hotspots," indicating these concepts are central to understanding and discussing autonomous vehicle technology. The nodes "safety" and "city street" are particularly noteworthy as they emphasize the critical aspects of safety and urban navigation in the context of autonomous driving. For the blind individual using a phone, the hotspots highlighted nodes such as "VoiceOver," "iPhone," "accessibility," and "pedestrians." These terms underscore the key elements in the context of smartphone usage by visually impaired individuals. "VoiceOver" and "accessibility" are central, highlighting the importance of these features in enabling effective smartphone use for blind users. This analysis underscores the comparable effectiveness of both methods in central theme identification but highlights the need for improvement in automated

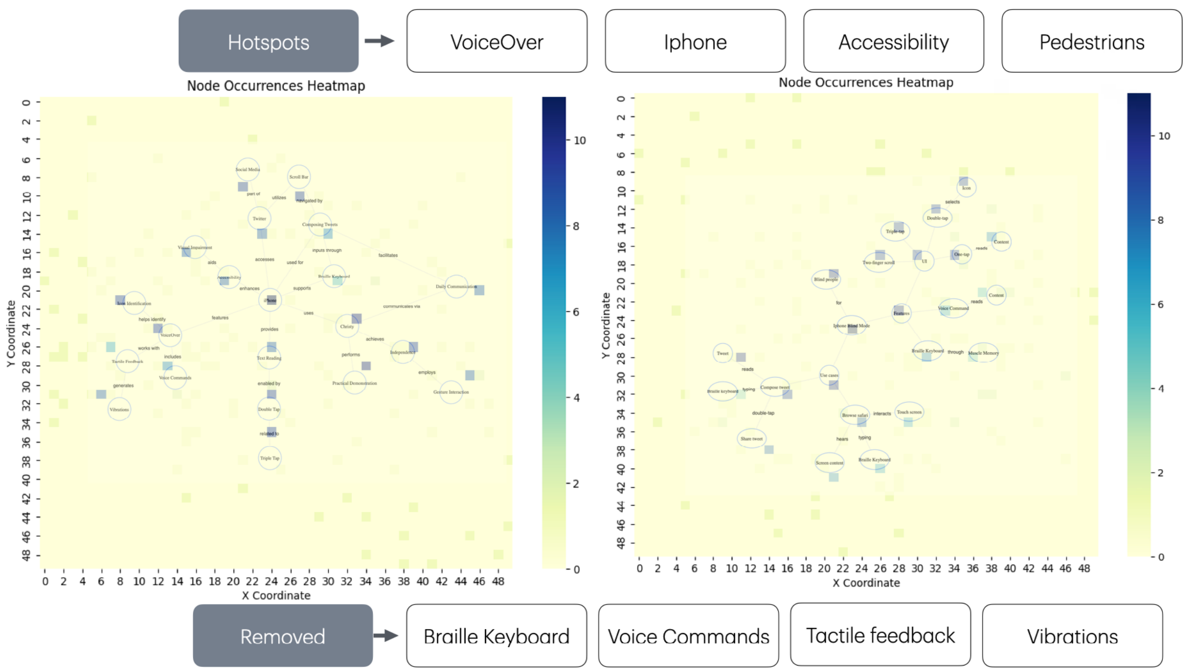


Figure 20: Heatmaps of Mindmaps from Blind woman context (Source: Author)

Figure 21: Heatmaps of Mindmaps from Autonomous Car context (Source: Author)

Interviews :

AI-generated mind maps are highly effective in capturing a comprehensive range of observations. Participants noted that AI tools often identify details that might be overlooked by human observers. The automated process can also lead to enhanced insights. For instance, Participant C2 mentioned, "It gives me direction, but it does not give me critical thoughts of the video," indicating that while AI-generated mind maps provide a solid foundation, designers still need to engage in critical thinking to refine and contextualize the information.

However, AI-generated mind maps often require further refinement and validation to be fully effective. On the other hand, the manual nature of traditional note-taking encourages critical thinking and deeper engagement with the content. Participant A5 mentioned, "It's better because in decision making there should be a human intervention." Human-made mind maps often have clearer categorization and logical structure. As Participant A6 commented, "It was more categorized and the problem was identified in a very clear way," highlighting the effectiveness of humans in organizing information coherently.

Summary

In conclusion, AI-generated mind maps and human-generated mind maps show comparable effectiveness in terms of triggers, relation links, and cross links. However, human-generated mind maps outperform AI-generated ones in organizing hierarchical information, as evidenced by the significant difference in the Hierarchy category. Participants perceived human-generated mind maps as more effective overall, as reflected in the UTAUT2 Performance Expectancy scores and the higher number of nodes added, indicating more detailed and comprehensive note-taking. Representing visual content on paper aids comprehension and retention, highlighting the importance of manual engagement in the note-taking process. The heatmap analysis underscores the comparable effectiveness of both the methods in central theme identification. LLM mindmaps also excel at capturing a broad array of observations quickly, but often require further refinement and validation to be fully effective.

Therefore, while AI-generated mind maps provide a solid foundation and enhance efficiency, human intervention remains crucial for deeper analysis and clear categorization of information. The situational context in which the mind maps are used also plays a significant role in determining their effectiveness. Traditional note-taking tends to be more effective in ensuring contextually relevant information and fostering critical thinking. In summary, AI-generated mind maps are excellent tools for initial data capture and organization, but human involvement is essential for ensuring the reliability and contextual relevance of the information.

(RQ.3) "*What impact do AI-generated mind maps have on the designer's cognitive load, enjoyment, and perceived usefulness compared to human-generated mind maps in aiding VBD?*"

A. COGNITIVE LOAD

Quantitative Analysis

Saccade Counts : The descriptive statistics for saccade counts during the editing tasks of human-generated and AI-generated mind maps are presented below:

- *Human-generated mind maps: M = 770.71, SD = 84.30*
- *AI-generated mind maps: M = 1042.64, SD = 84.30*

The mixed model analysis of saccade count during the editing task revealed a significant effect of who made the map ($F(1, 23.774) = 6.510$, $p = .018$), indicating a difference in saccade count between AI-generated and human-made mind maps. The context in which the mind maps were used did not have a significant effect on saccade count ($F(1, 23.774) = .018$, $p = .895$).

Frequent saccades indicate increased cognitive load as the brain must constantly reorient and process new visual information. The higher saccade count for AI-generated mind maps suggests that these maps may be more complex and less structured, requiring more frequent eye movements to comprehend and organize the information. Additionally, the significant effect of task number on saccade count ($F(1, 23.774) = 6.057$, $p = .022$) indicates that participants exhibited a higher saccade count for Task 1 (M = 1037.82, SE = 84.30) compared to Task 2 (M = 775.54, SE = 84.30), suggesting greater cognitive effort required for the first task.

Fixation Counts : The descriptive statistics for fixation counts during the editing tasks of human-generated and AI-generated mind maps are presented below:

- *Human-generated mind maps: M = 645.85, SD = 78.87*
- *AI-generated mind maps: M = 928.78, SD = 78.87*

The mixed model analysis of fixation count during the editing task revealed a significant effect of who made the map ($F(1, 22.560) = 7.835$, $p = .010$), indicating a difference in fixation count between AI-generated and human-made mind maps. The context in which the mind maps were used did not have a significant effect on fixation count ($F(1, 22.560) = .008$, $p = .929$). No significant effect of task number on fixation count was found ($F(1, 22.560) = 4.082$, $p = .055$).

The higher fixation counts observed for AI-generated mind maps suggest greater cognitive load, indicating participants exerted more mental effort to understand and edit these maps compared to human-generated ones. This increased cognitive load can translate to decreased performance, potentially leading to longer completion times and more errors. The significantly higher fixation count also suggests that editing AI-generated mind maps was perceived as more challenging, negatively affecting the overall user experience.

NASA TLX Mental Demand : The descriptive statistics for the NASA TLX scores of mental demand while using human-generated and AI-generated mind maps are presented below:

- *Human-generated mind maps: M = 56.79, SE = 3.80*
- *AI-generated mind maps: M = 60.54, SE = 3.80*

The mixed model analysis of mental demand revealed no significant effect of who made the mind map (F(1, 23.523) = 0.887, p = .356), indicating no difference in mental demand between AI-generated and human-made mind maps. Figure 22 also shows comparable scores of Human vs LLM in Mental Demand. The context in which the mind maps were used also did not have a significant effect (F(1, 23.523) = .002, p = .965). However, task number had a significant effect on mental demand (F(1, 23.523) = 10.134, p = .004). Participants perceived greater mental effort required for Task 1 (M = 65.00, SE = 3.80) compared to Task 2 (M = 52.32, SE = 3.80). Participants might have become more familiar with the editing process and the mind map interface as

NASA TLX Percieved Effort : The descriptive statistics for the NASA TLX scores of effort required while using human-generated and AI-generated mind maps are presented below:

- *Human-generated mind maps: M = 39.46, SE = 4.40*
- *AI-generated mind maps: M = 47.14, SE = 4.40*

The mixed model analysis of effort required revealed no significant effect of who made the mind map (F(1, 23.660) = 2.658, p = .116), indicating no difference in effort required between AI-generated and human-made mind maps. The context in which the mind maps were used did not significantly impact the effort required (F(1, 23.660) = 0.013, p = .910). Similarly, task number did not have a significant effect on effort required (F(1, 23.660) = 1.566, p = .223).

The analysis indicates that the type of mind map did not significantly affect participants' perceived mental demand or effort required. This suggests that both AI-generated and human-made mind maps perform similarly in terms of the cognitive load they impose on users.

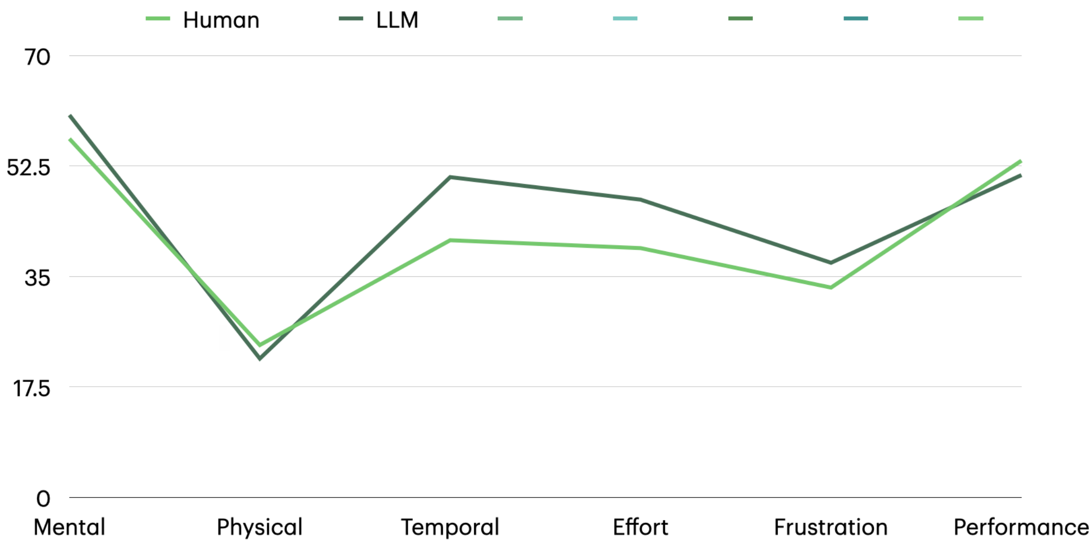


Figure 22: Mean NASA TLX scores of Human vs LLM (Source: Author)

UTAUT 2 Effort Expectancy : The estimated marginal means for UTAUT 2 Effort Expectancy (UTAUT_EE) based on who made the mind map indicated that human-generated mind maps (M = 3.88, SE = 0.14) were rated higher compared to AI-generated mind maps (M = 3.64, SE = 0.14). The pairwise comparison showed a significant difference between the two, with human-generated mind maps having a higher effort expectancy rating.

The mixed model analysis demonstrated a significant main effect of who made the mind map on UTAUT_EE (F(1, 23.845) = 4.707, p = .040). This finding underscores that human-generated mind maps are perceived as requiring less effort compared to those generated by AI. In contrast, neither context (p = .254) nor task number (p = .079) showed a significant main effect on UTAUT_EE. Additionally, the interaction effects between the factors (who made the map, context, and task number) were not significant.

Qualitative Results

Participants noted that the human-made mind maps were often more structured and hierarchical, which helped in reducing cognitive load. For example, Participant B3 stated, "The human mindmap had a clearer hierarchy and structure, making it easier to process the information." In contrast, the LLM-generated mind maps were sometimes seen as more cluttered and lacking in organization, potentially increasing cognitive load. Participant B5 mentioned, "The AI mindmap was comprehensive but lacked clear structure, requiring more effort to interpret."

AI-generated mind maps offer a structured starting point, which can reduce the initial cognitive load for designers. Participant D1 noted, "It gives you a start, but after that you have to kind of work on it. So I wouldn't say like it's 100% efficient. I would say it's 50% generated from video, 50% from your side." Participant B6 mentioned, "for sure it gives you a first start, which was really nice. Then you don't have to apply your brain from the starting." This suggests that AI tools help eliminate the initial effort of organizing thoughts and observations.

However, the extensive detail captured by AI-generated mind maps can sometimes lead to cognitive overload. Participants reported that these mind maps often contain an exhaustive list of observations, including minute details that might be unnecessary. Participant A3 mentioned, "Point out all the unnecessary, even the minuscule things which can be quite of a headache when you're trying to clean up your mind map." Participant D3 added, "It was just missing organization like the other map which had a hierarchical structure," highlighting the need for better categorization to avoid cognitive overload. The need to verify and edit AI-generated mind maps also contributes to cognitive load. Designers expressed the necessity to adapt and refine these mind maps to better fit their needs.

Summary

In conclusion, AI-generated mind maps tend to increase cognitive load compared to human-generated mind maps, as indicated by higher saccade and fixation counts during editing tasks. While both types of mind maps perform similarly in terms of perceived mental demand and effort required, human-generated mind maps are perceived as requiring less effort overall. AI-generated mind maps offer a good starting point and reduce initial cognitive effort but may lead to cognitive overload due to their detailed and often unstructured nature. Human-generated mind maps provide clearer structure and organization, helping to reduce cognitive load during the editing process.

B. PERCEIVED USEFULNESS

Quantitative Analysis

UTAUT 2 Behavioural Intention : A significant main effect was found for who made the mind map on UTAUT 2 Behavioural Intention (BI), $F(1, 24.257) = 6.038$, $p = .022$. Human-generated mind maps were rated higher in terms of behavioural intention ($M = 3.868$, $SE = 0.156$) compared to LLM-generated mind maps ($M = 3.595$, $SE = 0.156$), which can also be seen in the graph shown in Figure 23. Context ($p = .345$) and Task Number ($p = .254$) did not show significant main effects on UTAUT_BI, nor did the interaction effects between who made the map, context, and task number.

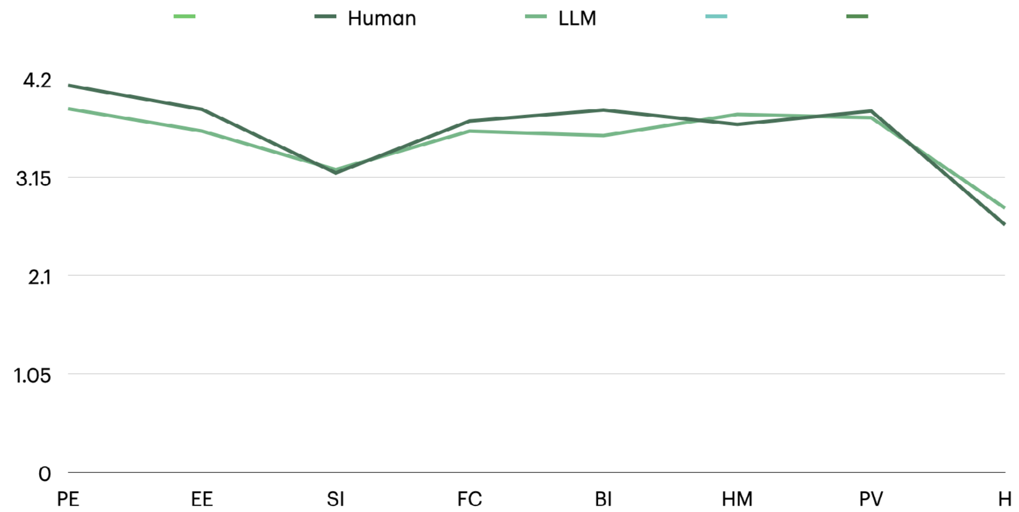


Figure 23: Mean UTAUT 2 scores of Human vs LLM (Source: Author)

Qualitative Insights

During the study, participants were asked to identify which mind map was created by a human and which one was generated by an LLM. Out of the total participants, 16 correctly identified the origin of the mind maps, while 12 guessed incorrectly. Participants who correctly identified LLM-generated mind maps pointed out the presence of redundant nodes, which were artifacts of the LLM's processing rather than intentional design decisions. They also noted the mechanical language used in descriptions, which lacked the nuanced and contextual understanding typically found in human-made mind maps. Additionally, the absence of iterative thinking, necessary to refine and structure information cohesively, was evident in LLM outputs. On the other hand, participants who guessed incorrectly thought the LLM was better at putting together all the video details into the mind map. They believed the LLM's skill in capturing many details from their experience showed it could do the job better. Some expected the AI would already surpass humans in tasks that involve gathering and organizing data.

The perceived usefulness of AI-generated mind maps is primarily attributed to their ability to capture comprehensive data from videos. Participants found that human-generated maps helped identify overlooked features and practical challenges. Participant A6 mentioned, "I found some features that I missed when watching the video." Participants appreciated the detailed attention to real-world conditions and the human-centered insights provided by these maps. For instance, Participant D4 noted, "Insight like how it attracts attention… are something that would have gone past me without the mindmap."

The initial structure provided by AI-generated mind maps is also seen as highly useful. Participants mentioned, “I think it’s a really good tool, like watching video and just getting all the information like in a very sorted manner in a very hierarchical manner” (Participant A4). LLM mind maps are effective in summarizing the core functionalities and decision-making processes, making them useful for quickly grasping the broader picture. However, they often lack the emotional depth and practical context, which can be crucial for user-centered design. As Participant A3 observed, “The mind map included many if not all of the important triggers in the video… For some points, more clarification is needed.”

AI-generated mind maps also support creativity and inspiration by providing a starting point that designers can build upon. Participant A1 stated, “It’s it’s like a tireless job for the machine that like it doesn’t get saturated.” This underscores the role of AI as a supportive tool that enhances the designer’s creative process by alleviating the burden of initial data capture and allowing them to focus on higher-level design thinking.

Summary

In summary, AI-generated mind maps have a notable impact on designers’ perceived usefulness compared to human-generated mind maps. While human-generated mind maps are rated higher in terms of behavioural intention, AI-generated maps are appreciated for their comprehensive data capture, initial structure, and support for creativity. However, they fall short in providing the emotional depth and practical context crucial for user-centered design. These insights suggest that AI-generated mind maps can serve as valuable tools to complement human efforts, particularly in data organization and initial design phases, while human-generated maps excel in offering nuanced and contextual understanding.

C. ENJOYMENT

Quantitative Results

NASA TLX Frustration : The NASA TLX analysis revealed that the source of the mind map ($F(1,24.153) = 0.592$, $p = 0.449$), the context in which it was created ($F(1,24.153) = 0.592$, $p = 0.449$), and the task number ($F(1,24.153) = 1.958$, $p = 0.174$) did not have a significant impact on TLX frustration scores. This suggests that perceived frustration was relatively consistent regardless of these factors.

UTAUT 2 Hedonic Motivation : The NASA TLX analysis revealed that the source of the mind map ($F(1,24.153) = 0.592$, $p = 0.449$), the context in which it was created ($F(1,24.153) = 0.592$, $p = 0.449$), and the task number ($F(1,24.153) = 1.958$, $p = 0.174$) did not have a significant impact on TLX frustration scores. This suggests that perceived frustration was relatively consistent regardless of these factors.

Qualitative Results

Out of the participants, 11 expressed a preference for the human-made mind map over the one generated by the LLM. In contrast, 6 participants favored the mind map created by the LLM. The remaining participants did not express a preference for either mind map. The enjoyment experienced by designers using AI-generated mind maps varies based on several factors, including the usability of the AI tool and the degree of alignment with the designer's thinking.

1. Efficiency and Time Savings: Many participants found AI-generated mind maps enjoyable due to the efficiency and time savings they offer. Participant A2 emphasized, "It capture all the things and if I don't want it, I can just discard it if I don't like, takes me much less time and I feel like it's way more efficient." The ability to quickly generate a comprehensive mind map with minimal effort was appreciated, contributing positively to the enjoyment of the tool.

2. Frustration with Structure and Usability: However, enjoyment was often tempered by frustration with the AI tool's structure and usability. Participant D2 mentioned, "second one was crazy because like it wasn't following my idea, so it was more random, so I had to adjust it and that was irritating and annoying," reflecting a common sentiment that the AI-generated mind maps sometimes lacked the intuitive structure and customization that designers expect. The need for further refinement and adjustment to fit personal preferences was a significant source of frustration.

3. Visual and Interaction Design: The visual and interaction design of the AI tool also played a crucial role in enjoyment. Participants pointed out several areas for improvement. Participant D3 commented, "UI has a lot to do with the content. Miss the UI hierarchy and the cycles," and Participant D4 added, "UI of that tool was annoying." These comments suggest that improving the user interface and interaction design of the AI tool could significantly enhance the overall enjoyment of using AI-generated mind maps.

Summary

In summary, AI-generated mind maps influence designers' enjoyment through their efficiency and time-saving capabilities, but their usability and intuitive structure are areas of concern. While the quantitative measures (NASA TLX and UTAUT 2 Hedonic Motivation) showed no significant differences, qualitative feedback highlighted a mixed response. The efficiency and initial comprehensive capture provided by AI tools are appreciated, but the frustration with structure and usability detracts from overall enjoyment. Improving the visual and interaction design of AI tools could enhance their appeal and usability, making them more enjoyable for designers.

(RQ.4) “*What factors influence the effectiveness of AI-generated mind maps in aiding designers’ decision-making processes?*”

Qualitative Insights

4.1. Trust

Trust is a crucial determinant in the effectiveness of AI-generated mind-mapping tools in the decision-making process of designers. The level of trust designers place in AI-generated mind maps can significantly impact how they utilize and integrate these tools into their workflow. Participant A5 highlighted the importance of verification, stating, “You need to verify what’s in the video and the mind map. You shouldn’t just blindly accept it.” This need for verification indicates a cautious trust, where designers see value in the AI tool but also recognize the necessity for human oversight.

Another participant emphasized the importance of human intervention in decision-making: “Because decision-making should involve human intervention” (Participant B2). This suggests that while the AI tool is useful, its effectiveness is enhanced when complemented by human judgment.

Moreover, transparency is critical in building trust in AI tools. Participant D5 mentioned, “If it is clearly communicated that it is not going to be 100% perfect, but it’s going to give you a start, then it’s a good tool.” Clear communication of the tool’s limitations can enhance its perceived value and reliability, fostering a balanced and informed use of AI-generated mind maps.

4.2. Reliance

Reliance on AI-generated mind maps can be a double-edged sword. It can either enhance or hinder a designer’s performance, depending on their existing skill level and how they balance the use of the tool with their creative process. Participant D5 pointed out, “What makes a good detective for a human being is already being able to filter out everything and see the details that matter.” This indicates that reliance on AI should be balanced with the designer’s ability to discern critical details.

Another participant noted that the tool can improve performance for less experienced designers but might lower the performance of high-performing individuals: “Generally observed, it improves performance if you’re weak but lowers your performance if you’re a high-performing individual” (Participant C3). This suggests that while AI tools can be a valuable aid, over-reliance could stifle creativity and reduce the quality of work for more skilled designers.

A balanced approach is necessary, as highlighted by Participant D1 who said, “A balance in between because you are hindering creativity if you sometimes just being open forces you to be open to everything, and when you start from scratch, you already have some topics, and you might be focused on those topics.” This quote illustrates the balance required in relying on AI-generated mind maps for design. It acknowledges that while the AI tool provides a structured starting point, over-reliance can hinder creativity by limiting the exploration of new ideas. This illustrates that while AI-generated mind maps can provide a useful starting point, designers must balance their use with creative freedom to explore new ideas fully.

4.3. Workflow

The integration of AI-generated mind maps into the design workflow is a critical determinant of their effectiveness, requiring intuitive usability, flexibility, and the ability to enhance rather than hinder the creative process. The ease of use and the designer’s familiarity with the tool can significantly impact its utility. Participant B4 expressed initial difficulty in understanding the AI-generated mind map, saying, “I couldn’t get insights from the mind map because I didn’t know how to read the mind map (add arrows).” This highlights the need for an intuitive design that facilitates quick comprehension and efficient navigation.

Training and gradual adaptation play a crucial role in integrating new tools into the workflow. As Participant B5 noted, "It's about how my perception changed when I learned how to use this. It was more difficult at first, and then I found the value of it; it became easier for me." This indicates that with proper training and continuous use, designers can become proficient in utilizing AI-generated mind maps, thereby enhancing their workflow.

Flexibility in editing and customizing the mind maps is essential for their effectiveness. Participant D2 highlighted this by saying, "And then you can just change stuff, add things, say, 'This is wrong. This is right,' and that's easier for the designer than starting from scratch." This flexibility allows designers to tailor the AI-generated content to fit their specific needs, promoting a more efficient and personalized workflow. The ability to modify the mind maps ensures that designers remain actively engaged with the content, refining and adapting it to suit their creative vision.

However, the organization of the AI-generated content is also crucial. Participant C5 noted, "If it generates something that I think is unorganized and that I need to improve on after it finishes, then I don't think I would use it." This statement underscores the importance of producing well-structured and coherent outputs. An organized mind map reduces the cognitive load on designers, allowing them to focus on creative aspects rather than spending time reorganizing information.

Editing AI-generated content facilitates a deeper engagement with the material, reinforcing the designer's understanding and integration into the design process. As Participant A3 mentioned, "It is nice that when you actually edit the things, you kind of read everything through, and that thing helps." This iterative interaction between the designer and the tool promotes a thorough understanding and better assimilation of the information. Moreover, this process enables designers to question and validate their interpretations, ensuring that their understanding is accurate and comprehensive. Participant B4 emphasized this by saying, "It's best if you verify a couple of things, so don't trust it completely." This validation process is crucial in confirming the correctness of the AI's interpretations and integrating them into the designer's broader understanding.

Efficiency and time-saving are also significant considerations. Participant C4 appreciated the tool's ability to save time, stating, "It would at least save me time from typing." The AI tool should streamline the workflow, providing an initial structure that designers can build upon, thereby enhancing productivity without compromising the creative process. By allowing designers to quickly generate a structured overview, the tool enables them to focus on higher-level creative tasks, such as refining ideas and exploring new connections.

Similarities of Findings with Literature Review

The findings from the participant interviews align with the literature on the effectiveness of mind maps in enhancing learning and retention. Trust and reliance on AI-generated tools, as discussed by the participants, are echoed in the literature on human-AI co-creative systems. Effective interaction design and communication dynamics are critical determinants of these systems' success, as highlighted by Rezwana & Maher (2022). The cautious trust and need for human oversight mentioned by participants reflect the importance of appropriate trust and reliance, distinguishing between them to ensure effective use (Bansal et al., 2022; Scharowski et al., 2022). The balance between AI tool reliance and creative freedom aligns with findings that overreliance can stifle creativity and reduce quality, while appropriate use can enhance performance (Vasconcelos et al., 2023; Gaole et al., 2023). The literature also supports the importance of flexibility and customization in integrating AI tools into workflows, enhancing their effectiveness and usability (Gmeiner et al., 2022; Negalur et al., 2022).

Finally, the necessity for intuitive design and proper training, as highlighted by participants, aligns with the literature on the learning curve associated with new co-creative AI systems and the importance of effective user engagement and support (Anggy et al., 2022; Gmeiner et al., 2022). These connections underscore the importance of integrating AI tools in a way that enhances rather than hinders the creative process, aligning with both user experiences and established research.

5.3 Reflection on Hypotheses

5.3.1

"The mind map reduces the time and analytical rigor required for the analysis considerably."

Hypothesis 1

The findings from our study provide strong evidence in support of the hypothesis that LLM-generated mind maps significantly reduce both the time and analytical rigor required for understanding video content. Participants highlighted several key advantages of the AI-generated mind maps, emphasizing their efficiency and the reduction in manual effort.

Participant A2 remarked that the tool "captures all the things" and enables quick discarding of unwanted elements, making the process "much less time-consuming" and "way more efficient." This underscores the significant time savings and increased efficiency provided by the AI tool. Another participant, D6, highlighted the minimal effort required to generate a mind map, describing it as "insanely valuable" due to the simplicity of generating a mind map with just "one click." This participant noted that, while the tool could benefit from "a bit more structure and focus," it still offers considerable value by streamlining the initial stages of content analysis.

Participants also recognized the potential for the tool to alleviate the tedium and time demands of manual video analysis. Participant C1 noted that AI-driven analysis would be "less time intensive" and reduce the physical and mental strain associated with traditional methods. However, they also stressed the importance of the AI doing "a good job" and the need for users to "trust it," highlighting the necessity for accuracy and reliability in AI outputs.

The collaborative aspect of the tool was also emphasized. Participant D5 mentioned that the AI-generated mind maps "give you a start," but require the user to refine and build upon them, suggesting a 50/50 contribution from the AI and the user. This indicates that while the AI significantly reduces the initial analytical burden, it still necessitates active user engagement to achieve optimal results.

Furthermore, participants appreciated the AI's tireless nature, with B3 noting that it performs a "tireless job" without getting "saturated," highlighting the consistent and continuous analysis capabilities of the AI.

In summary, participant feedback strongly supports the hypothesis that LLM-generated mind maps reduce the time and analytical rigor required for video content analysis. The tool offers a valuable resource for designers, enhancing their workflow efficiency and reducing the strain of manual analysis.

5.3.2

"The mind map might provide the designer with a clear and structured overview of the video, highlighting key concepts in an easily digestible format."

Hypothesis 2

The results of the study support the hypothesis that designers might question the links and connections in the AI-generated mind map, and in the process of adding new connections, they reframe their understanding, which aids in better retention of video content. Participants highlighted several aspects that validate this hypothesis.

Participant B4 described their workflow of using AI-generated mind maps in conjunction with video analysis to gain deeper insights: "First I do an AI-generated mind map and then I put the mind map and the video together and I validate the mind map with the video playing, so that I get like a deeper insight." This highlights the iterative process of validation and deeper engagement with the content.

Another participant, C2, emphasized the importance of not over-relying on the AI-generated mind map without verification: "If you give me my pen and say hey, it's best if you verify a couple of things, so don't trust it completely. Then that would be a good tool." This process of verification ensures that designers are actively engaging with the content, reducing over-reliance on the AI and enhancing understanding.

Additionally, participant B5 noted the benefits of editing the AI-generated mind map, stating, "It is nice that when you actually edit the things, you kind of read everything through and that helps to restructure it in your mind." This editing process reinforces content comprehension and memory retention.

Another participant, A1, found it easier to refine and personalize the mind map rather than starting from scratch: "You can just change stuff, add things, say this is wrong, this is right, and that's easier for the designer than actually starting from a video from scratch." Collectively, these insights affirm that questioning and modifying the AI-generated mind map not only helps designers to reframe their understanding but also improves their ability to remember the video content more effectively.

5.3.3

"The designer might question the links and connections in the mind map, and to add new connections/links, they have to reframe their understanding. This process, along with cross-checking the LLM's interpretations with their own, might help them remember the contents of the video better."

Hypothesis 3

The results of the study strongly support the hypothesis that LLM-generated mind maps provide designers with a beneficial structure of video content while allowing for cross-checking of interpretations. Participants highlighted several key advantages of using AI-generated mind maps.

Participant D3 emphasized the comprehensive coverage and organizational clarity, noting that the mind maps help identify covered concepts and structure: "I know what are the concepts covered and what was the structure of the video, so it's good in that aspect." Another participant, D4, mentioned the utility in retaining information from longer videos, as they can refer back to the mind map to ensure no content is missed: "If it is more than five or 10 minutes, I'll probably forget certain elements... I can always go back to the summary." This highlights the mind map's role in preventing information loss and aiding memory retention.

Further supporting the hypothesis, another participant, D5, appreciated the ease of initial understanding, indicating that the AI-generated mind maps facilitate a more efficient design process: "It gives you a first start... you don't have to apply your brain from the starting." Additionally, participants recognized the value of AI's perspective, with one noting that they noticed elements in the AI-generated mind map that they had missed themselves: "I saw something that I didn't notice."

Collectively, these insights affirm that LLM-generated mind maps not only provide a clear and structured overview of video content but also enhance designers' ability to interpret and utilize the information effectively.

5.4 Areas for Improvement

5.4.1 Structure and Hierarchy

The study revealed a major downside of LLM-generated mind maps, which is their lack of hierarchy and structure compared to human-created ones. This issue was evident in both the feedback from participants and the analysis. Participants consistently praised the superior organization of human-made mind maps.

Participant D1 pointed out that the human-made mind map was “better categorized and the issue was clearly identified,” highlighting the clarity and definition missing in the AI-generated version. Another participant, D2, described the human-made map as “more organized and clearer,” emphasizing the streamlined nature of the human approach. The logical structure was also valued, as participant A1 noted it “had better logic to its structure,” which is vital for effective mind mapping.

Several participants noted specific shortcomings in the AI-generated maps. Participant C3 mentioned, “It just lists all the tasks without organizing them effectively,” highlighting the AI’s failure to categorize information hierarchically. Another, C2, commented, “There was some hierarchy in the human map, which was lacking in the second one,” addressing the lack of structured organization in the AI-generated maps. The need for more human intervention was also recognized, with participant B1 suggesting, “Maybe one more level of human intervention could make it more effective,” indicating that substantial manual adjustments are necessary for the AI-generated maps to be useful.

Participants expressed frustration with the chaotic and cluttered nature of the AI-generated maps. Participant C4 mentioned that it “wasn’t following my idea, so it was more random, so I had to adjust it,” which was “irritating and annoying.” Another participant, B2, elaborated, “The first one had more branches and subdivisions, so somewhat like. Not so noteworthy,” indicating that the AI map was overly detailed without proper structure. Participant B3 stated, “It identified a lot of stuff. But the logic was poor,” showing the AI’s struggle to organize observations logically. Similarly, participant D4 commented, “It was a more comprehensive list of observations of the video than a mind map,” emphasizing the AI’s tendency to create exhaustive but disorganized lists.

Criticism was also directed towards the cluttered nature of the AI maps. Participant C5 stated, “Mind maps are something we use to make sense of something, but if it’s becoming too much clumsy, it’s not making sense anymore. You have to first clean the clutter and then again you…,” demonstrating the extra effort needed to make AI-generated maps usable. Participant C6 expressed the desire to “remove a lot of stuff I just couldn’t, but I would have done that if I could,” indicating the rigidity and clutter of the AI maps. Finally, participant B4 observed, “The second one was chaotic because it wasn’t following my idea, so it was more random,” highlighting the frustration caused by the lack of alignment with their thought process.

Collectively, these insights reveal that while LLM-generated mind maps are comprehensive, their lack of proper categorization and hierarchical structure diminishes their usability, often requiring significant human effort to make them functional.

5.4.2 User Interface and Visual Weight

The study also identified poor intuitiveness of the UI and the lack of features such as easy addition of color and line width adjustments as significant drawbacks of LLM-generated mind maps. These issues underscore the importance of user interface (UI) in the acceptance of new technology and the role of visual hierarchy in effective mind mapping. Participants frequently highlighted these shortcomings.

Participant C1 pointed out that the "UI could be improved... like the colour, colour, contrast and then like the workflow," indicating that the visual aspects and user experience were not optimal. Another participant, D2, mentioned the presence of "certain glitches," which further detracts from the usability of the tool.

The impact of UI on the content's effectiveness was also noted by participant C3, who said: "UI has a lot to do with the content. Miss the UI hierarchy and the cycles. Fat markers, thin markers we should highlight," emphasizing the importance of visual differentiation in mind maps. Another participant, A2, found the lack of mobility frustrating, stating, "The UI of that tool was annoying," and emphasizing that mobility within the mind map tool is crucial for efficient use: "It's more important [to have] mobility, so being able to move all the time around, it's more important than actually editing."

The lack of color customization was a recurrent theme. Participant A1 noted, "Could be a bit more intuitive and, you know, everything is like the same color," highlighting the need for more intuitive color-coding options. Another participant, B1, mentioned the difficulty in prioritizing information due to uniform visual weight: "You could color it into priority, but I think it's more weight," indicating that visual weight and color coding are essential for distinguishing inputs and outputs. The sentiment was echoed by participant D3: "I would change the colors or yeah, make them bigger or the font change."

Participants also pointed out the absence of visual hierarchy features. Participant B4 mentioned, "Could add a little bit more like visual hierarchy with the colors and things," and suggested that different line types and shapes could enhance the tool's effectiveness: "So let's say dotted line or colored line or something like that... all of them were of the same shape." This lack of differentiation made it difficult for users to organize and prioritize information effectively.

Collectively, these insights reveal that the poor intuitiveness of the UI and the lack of features such as easy addition of color and line width adjustments significantly hinder the effectiveness and usability of LLM-generated mind maps. Enhancing these aspects could lead to better acceptance and utilization of the tool, making it more practical and beneficial for users.

5.4.3 Correctness and Language

The study also pointed out a notable drawback in the mind maps created by the LLM, concerning accuracy in language, redundancy, lack of precision, and contextual grasp. This issue highlights the fundamental distinctions between AI and human processing, especially in tasks that require subtle nuances and contextual sensitivity. These deficiencies were frequently observed by participants, with one noting that the AI offers guidance but lacks critical analysis of the video, revealing its incapacity to delve deeper. Participant D4 mentioned, "AI just gives you guidance, but it lacks critical analysis," pointing out this limitation.

Another participant, C3, highlighted that the AI presents information in a direct manner, missing the critical and nuanced understanding that a human would provide. Instances of inaccuracies and repetition were specifically mentioned by participants. Participant B2 recalled an irrelevant detail involving a black fan and a white fan that made no sense, indicating the AI's struggle with maintaining relevance in context: "It talked about a black fan and a white fan, which made no sense."

Another participant, D3, mentioned that the AI simply regurgitated information without coherence, resulting in fragmented and at times illogical outputs: "It just repeats information, sometimes making it fragmented and illogical." Furthermore, participant C5 questioned the presence of inexplicable content generated by the AI, expressing confusion over its relevance: "There was stuff in there that I just couldn't understand why it was included." Criticism was also directed towards the mechanical nature of the AI's language. Participant A1 found the language difficult to grasp and somewhat alienating, while another, C4, observed that the AI's language seemed somewhat mechanical compared to the more organic and human-like language of a mind map created by a human: "The AI's language was too mechanical, not like how a human would write it."

Participants highlighted the AI's deficiency in contextual understanding as well. Participant B4 noted that the AI merely processes the script, maps out words, and generates keywords, a task that may not be performed by a human, indicating the AI's reliance on superficial processing: "It just processes the script and maps out words, not really understanding the context." Another participant, D2, commented that the human-generated mind map was better at highlighting nuances, emphasizing humans' superior ability to capture subtle details: "The human map highlighted nuances that the AI missed." The AI's inability to establish connections beyond explicit content was noted, reflecting the broader and more integrated perspective that humans bring to mind mapping. Participant B5 mentioned having a hierarchical way of viewing and mapping things, contrasting with the AI's more linear and less structured approach: "I have a hierarchical way of organizing things, which the AI lacks."

Overall, these observations demonstrate that while LLM-generated mind maps can be extensive, their lack of critical thinking, contextual understanding, and nuanced language significantly restrict their effectiveness compared to mind maps created by humans. These limitations underscore the distinct cognitive abilities of humans that AI has not fully replicated yet.

5.4 Effect of Task Order

The analysis of the mixed model results reveals significant effects of task order on several key parameters, indicating that participants experienced a learning effect as they progressed through the tasks. Specifically, TLX mental demand ($F(1, 23.523) = 10.134$, $p = 0.004$) was higher for the first task ($M = 65.00$, $SE = 3.80$) compared to the second task ($M = 52.32$, $SE = 3.80$), reflecting greater perceived mental effort initially. TLX temporal demand ($F(1, 23.651) = 5.448$, $p = 0.028$) was also higher for the first task ($M = 51.60$, $SE = 4.92$) than for the second task ($M = 39.82$, $SE = 4.92$), indicating more time pressure during the first task. The overall TLX scores ($F(1, 23.345) = 4.731$, $p = 0.040$) were higher for the first task ($M = 45.80$, $SE = 2.92$) compared to the second task ($M = 40.22$, $SE = 2.92$), showing a higher overall workload at the beginning. The graph of Mean TLX scores across human vs LLMs is shown in figure 24 below.

Additionally, edit task times ($F(1, 23.204) = 6.569$, $p = 0.017$) were longer for the first task ($M = 445.14$ seconds, $SE = 12.45$) compared to the second task ($M = 326.73$ seconds, $SE = 12.45$), indicating longer completion times initially. Saccade counts during editing ($F(1, 23.774) = 6.057$, $p = 0.022$) were higher for the first task ($M = 1037.82$, $SE = 84.30$) compared to the second task ($M = 775.54$, $SE = 84.30$), suggesting greater cognitive effort during the first task. As participants gained experience, these metrics improved, with lower TLX scores, reduced edit times, and fewer saccades on the second task, underscoring increased efficiency and reduced cognitive load. This trend suggests that participants became more adept at managing the tasks and tools, highlighting the impact of familiarity and practice on performance and cognitive demands.

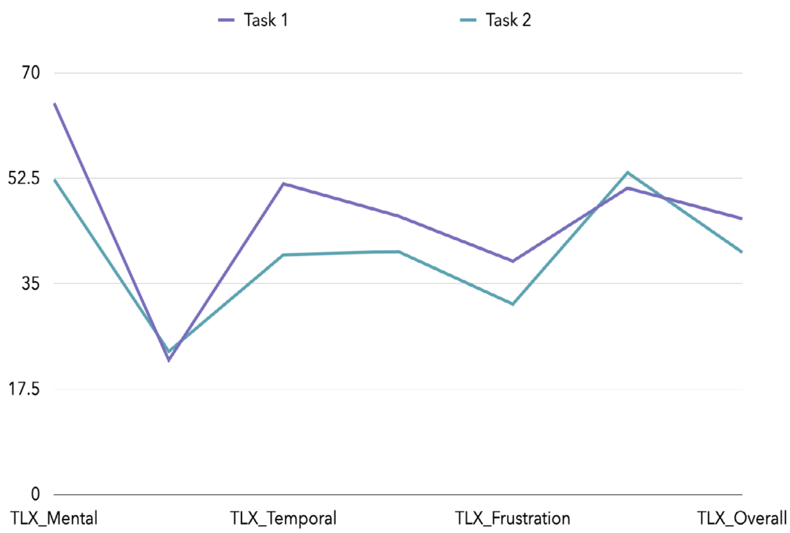


Figure 24: Mean NASA TLX Scores for Task 1 vs Task 2 (Source: Author)

5.5 Effect of Context

The analysis of the mixed model results reveals that the context in which the tasks were performed, specifically the autonomous car context (Context 1) versus the blind woman context (Context 2), significantly influenced some parameters but not others. Most notably, the NASA TLX performance scores indicated a significant effect of context ($F(1, 23.587) = 7.812$, $p = 0.010$). This highlights that the situational context in which the mind maps are used plays a more crucial role in determining their effectiveness than whether the mind maps were created by AI or humans.

For TLX performance, the autonomous car context had a mean score of M = 48.07 (SE = 4.03) while the blind woman mind maps had a mean score of M = 56.28 (SE = 4.03). The significant effect of context on TLX performance suggests that participants' perceived workload and task performance varied depending on the context, regardless of the source of the mind maps. Additionally, the pre-task trigger had a significant effect of context ($F(1, 24.695) = 8.197$, $p = 0.008$). The mean pre-task trigger score was higher in the blind woman context (M = 73.74, SE = 2.925) compared to the autonomous car context (M = 64.85, SE = 2.92). This suggests that the situational context influenced participants' initial engagement or readiness before starting the task, which could be due to varying levels of interest, perceived relevance, or emotional engagement with the content.

In contrast, other measures such as UTAUT Performance Expectancy (PE) and the number of nodes added did not show a significant effect of context. Overall the mindmap generated for blind woman context scored better in the rubric as shown in Figure 25. Both contexts perform comparable to each other when it comes to UTAUT 2 acceptance levels, as shown in Figure 26.

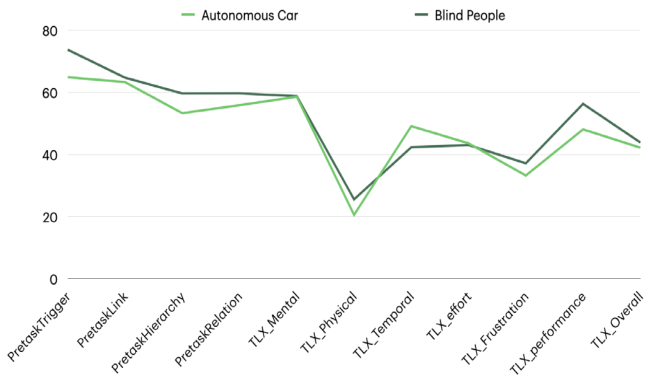


Figure 25: Mean MMR and NASA TLX Scores for Context 1 vs Context 2 (Source: Author)

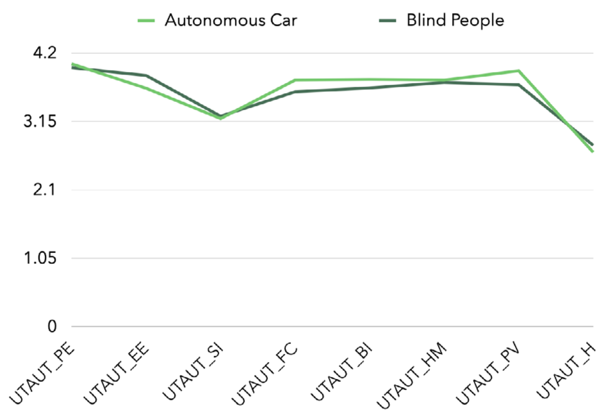


Figure 26: Mean UTAUT 2 Scores for Context 1 vs Context 2 (Source: Author)

5.6 Parameters Significantly Affected by Mind Map Creator

The analysis of key parameters reveals significant differences in the quality and effectiveness of mind maps generated by humans versus those created by Large Language Models (LLMs) as shown in figure 27 below. Human-generated mind maps exhibit superior organization in terms of hierarchy, which is crucial for users to quickly comprehend and navigate information. This organizational clarity translates to higher performance expectancy, as users believe human-made mind maps are more likely to help them perform better in their tasks.

Effort expectancy further supports this preference, with human-generated mind maps requiring less cognitive load to understand and use. Consequently, users demonstrate a higher behavioral intention to continue using human-generated mind maps in the future, reflecting their perceived reliability and effectiveness.

Edit task time also highlights the advantages of human-generated mind maps, as they require significantly less time to edit compared to LLM-generated ones. This efficiency can be attributed to the better initial organization and clarity provided by human creators, reducing the need for extensive modifications.

Additionally, lower saccade and fixation counts during the editing process for human-generated mind maps indicate fewer disruptions and easier reading, which contributes to faster information processing. This reduced cognitive load is critical in complex design tasks, where efficiency and clarity are paramount.

Interestingly, the number of nodes added during editing is higher for human-generated mind maps. This finding correlates with participant feedback that, while LLMs do an excellent job of comprehensively listing and connecting information from the video, they sometimes fall short in terms of organization and hierarchy. Consequently, human-generated maps require more node additions to achieve the same level of comprehensiveness, yet they start off with better structure and clarity.

In summary, while LLM-generated mind maps offer efficiency and comprehensive initial captures of information, they often fall short in terms of organization, ease of use, and overall user preference. Human-generated mind maps provide a more structured, comprehensive, and user-friendly experience, significantly reducing the cognitive load and effort required for effective use.

Dependent Variables	Human	LLM	P value	Significance	Definition
Hierarchy	62.143	50.786	0.012	Significant	Organisation of content, groups and sub-groups
Performance Expectancy	4.13	3.88	0.018	Significant	Users believe human-made mindmaps are more likely to help them perform
Effort Expectancy	3.87	3.64	0.04	Significant	Effort required to understand and use LLM-made mindmaps is perceived to
Behavioural Intention	3.86	3.59	0.022	Significant	it means users are more likely to plan to use human-made mindmaps in future
Edit task time (s)	328.37	443.5	0.02	Significant	Time taken to delete, add and rearrange structure
Saccade count_edit_task	770.7	1042.64	0.018	Significant	More disruptions, difficulty reading slower processing of information
Fixation count_edit_task	645.8	928.7	0.010	Significant	Cognitive load, challenging task, harder task, reduced performance
Number of Nodes added	5.35	2.78	0.046	~ Significant	Information missing from the mindmap

Figure 27: List of Dependent Variables significantly affected by the Mindmap Maker (Source: Author)

6

Research conclusion

Discussion | Limitations | Recommendation | Future Work

“ Azhavai minjinal Amuthamum Keduthu ”

- Tamil Proverb

“ Even nectar becomes poison when taken in excess. ”

- English Translation

6.1. Discussion

This thesis offered insightful information about how LLM generated mindmaps could be used in video analysis. The section that follows contains the conclusions pertaining to the main study topics and their subquestions.

From our literature survey, we identified that the most crucial feature of a mind map is its structure. Ironically, our study revealed that the weakest point of AI-generated mind maps was also their structure. This structure significantly influenced participants' ability to grasp and understand the mind maps quickly. As large language models (LLMs) continue to improve their reasoning capabilities, we can anticipate enhancements in this area. When considering the quality of nodes, LLMs performed on par with human designers, demonstrating the effectiveness of computer vision models in capturing the content and context of the video. These models were able to identify and convey key elements from the video, forming valid connections. However, the mind maps resembled a tangled tree rather than a tree with clear subbranches, making them less intuitive for human users.

Moreover, despite the AI's ability to avoid irrelevant nodes, the generated mind maps contained redundancies and unnecessary details. The AI lacked an understanding of the purpose behind the mind map, leading to an excess of information that did not always align with the design context. By refining prompts and iterating on the outputs, we could potentially achieve more nuanced results. Nevertheless, the AI tool is designed to aid, not replace, human designers. It aims to reduce cognitive load and effort in video-based design but cannot match the human capacity for understanding context and lateral thinking.

Additionally, participants appreciated having an AI-generated mind map to edit and refine, finding it a useful starting point for note-taking and memory retention without additional effort. However, the AI-generated maps were not entirely reliable on their own. Designers needed to review and verify the connections made by the AI, taking its outputs with caution to avoid over-reliance and potential disappointment. Furthermore, improvements in the user interface, including visual hierarchy and structural clarity, would enhance the usability of AI-generated mind maps, making them more appealing to users.

The study also showed a positive trend as users reported lower scores in the NASA TLX dimensions in their second task, indicating better adaptation to the mind map tool's interface and workflow. The time required to edit the mind maps decreased, likely due to users becoming more familiar with the tool rather than fatigue, as suggested by favorable NASA TLX and UTAUT scores. Interestingly, despite differences in mind map quality and context between tasks involving a video about a blind woman and one about an autonomous car, these differences did not significantly affect the overall perceived cognitive demand or UTAUT scores. This suggests that AI-generated mind maps could be beneficial for long and monotonous videos, providing a quick understanding of key elements and occurrences.

In addition, the study highlighted the value of a brief, two-minute video in providing designers with enriched information about context and demographics, facilitating empathy with the user. The mind map tool offered a new perspective, helping designers focus without bias. Validating and questioning the AI-generated connections prompted deeper insights and new interpretations. The edited mind maps, checked and validated by users, became useful artifacts containing structured, digestible information.

Overall, by combining the objective, comprehensive observations from the AI with the critical, nuanced reasoning of human designers, valuable results can be achieved in a shorter time frame. This hybrid approach leverages the strengths of both AI and human cognition, addressing major hurdles identified in the literature survey. By continuing to refine AI tools and integrating them seamlessly into design workflows, we can enhance their effectiveness and reliability, ultimately benefiting the design process.

Subquestion 1 :
How do AI-generated mind maps compare to human-generated mind maps in terms of efficiency and effectiveness in aiding video-based design (VBD)?
AI-generated mind maps offer significant efficiency gains in video-based design (VBD) by automating note-taking and filtering irrelevant information. However, they require more time for editing and analysis compared to human-created counterparts. While AI excels at rapid data capture and initial organization, human expertise is indispensable for in-depth analysis, categorization, and ensuring contextual relevance. Human-generated mind maps demonstrate superior performance in organizing hierarchical information and fostering critical thinking, although AI-generated maps effectively identify central themes. Ultimately, the optimal approach involves combining the strengths of both methods to maximize efficiency and effectiveness in VBD.

Subquestion 2 :
What impact do AI-generated mind maps have on the designer's cognitive load, enjoyment, and perceived usefulness compared to human-generated mind maps in aiding VBD?
AI-generated mind maps present a double-edged sword for designers. While they significantly boost efficiency and initial data capture, they can also increase cognitive load due to their unstructured nature. This trade-off impacts both enjoyment and perceived usefulness. While designers appreciate the time saved by AI tools, they often find human-generated mind maps more effective for in-depth analysis and understanding. Although AI mind maps can stimulate creativity through comprehensive data presentation, their lack of intuitive structure can hinder the design process. To optimize the designer experience, a hybrid approach is recommended, leveraging AI for rapid information gathering and human expertise for strategic thinking and creative development.

Subquestion 3 :
What factors influence the effectiveness of AI-generated mind maps in aiding designers' decision-making processes?
The effectiveness of AI-generated mind maps in aiding designers' decision-making hinges on a delicate interplay of trust, reliance, and workflow integration. Designers must develop a cautious trust in the AI tool, recognizing its strengths while maintaining critical oversight. Balancing reliance on the AI with human judgment is crucial to optimize performance and prevent creative stagnation. Seamless integration into the design workflow demands intuitive usability, flexibility, and the ability to enhance, rather than hinder, the creative process. By fostering trust, striking the right balance of reliance, and optimizing UI and visual hierarchy in workflow, AI-generated mind maps can become invaluable assets for designers, augmenting performance and efficiency. These findings align with existing research on human-AI collaboration, emphasizing the importance of effective interaction design and user support.

6.2. Design recommmendation

(1) For Improving the Structuring of Mind Maps:
The structure of a mind map is fundamental to its effectiveness, as it determines how easily users can understand and interact with the information presented. In our study, the AI-generated mind maps often lacked a clear and intuitive structure, appearing more like a web of interconnected ideas rather than a coherent flow of information. This issue can be addressed by drawing inspiration from tools like EdrawMind AI, which create logically structured mind maps with clear visual hierarchies. EdrawMind AI uses algorithms to ensure that the mind map's layout is both visually appealing and functionally effective, helping users quickly grasp the relationships between different concepts (Edrawmind AI - Ai-powered Mind Mapping Made Simple and Intuitive, 2024). Implementing similar structuring algorithms in our tool could significantly enhance the clarity and usability of the generated mind maps.

(2) Iterating Outputs for Better Accuracy (Agent-Based Workflow):
An agent-based workflow involves iterative refinement of AI outputs through multiple cycles of feedback and adjustment. This approach can greatly enhance the accuracy and relevance of mind maps. For example, Creately VIZ employs AI to generate insights and summarize collaborative sessions, creating detailed mind maps that evolve with each iteration (AI Generated Mind Maps | Collaborative AI Mind Mapping Tool | Creately, 2024). By incorporating an agent-based workflow, our tool could benefit from continuous improvement, where each iteration refines the mind map based on user feedback and additional data. This iterative process can help in identifying and correcting errors, making the mind maps more accurate and contextually appropriate. Moreover, this iterative refinement adds the users' contextual understanding to the LLM's objective output, thus enhancing the overall utility and relevance of the mind maps.

(3) More Intuitive Interface of the Tool:
The user interface (UI) is crucial for the usability of AI tools. A well-designed, intuitive UI can reduce cognitive load and make it easier for users to interact with the tool. Xmind, for instance, emphasizes on intuitive design and visual hierarchy that allows users to effortlessly navigate and utilize its features without a steep learning curve (Xmind - Full-featured Mind Mapping and Brainstorming Tool, 2024). By adopting similar UI principles, our tool can become more user-friendly. Features like drag-and-drop functionality, easy node addition and deletion, and clear visual cues can make the tool more accessible, enabling users to focus on the content rather than struggling with the interface.

(4) Timestamps and Summaries Feature:
Adding timestamps and brief summaries to each node and edge can significantly enhance the usability and trustworthiness of mind maps. This feature allows users to see the reasoning behind each interpretation and verify it against the video content. For example, incorporating a feature where clicking on a node reveals a timestamped excerpt of the video can provide context and justification for that node's inclusion. This approach can increase user confidence in the AI's outputs and facilitate efficient content verification. Tools like Notion AI already implement similar features, linking content summaries and notes to specific points in the source material, thereby enhancing the user's ability to cross-reference and validate information (Notion AI | Now with Q&A, 2024).

(5) Encourage Slow Expansion:
Starting with a basic, preliminary mind map that captures the core subject and allowing users to gradually expand it can prevent cognitive overload and make the information more digestible. This method aligns with cognitive load theory, which suggests that learning is more effective when information is presented in manageable chunks. Creately, for instance, offers features for expanding mind maps based on user commands, allowing for incremental development of the mind map (AI Generated Mind Maps | Collaborative AI Mind Mapping Tool | Creately, 2024). By adopting a similar approach, our tool can help users build a comprehensive mind map without feeling overwhelmed by too much information at once. This gradual expansion can also encourage users to engage more deeply with the content, adding and refining nodes as they gain a better understanding of the material.

6.3. Limitations

Despite the promising findings of our study, several limitations should be noted. Firstly, the sample size of participants was relatively small, which may impact the generalizability of the results. With a larger and more diverse participant pool, we could gain a more comprehensive understanding of the effectiveness of AI-generated versus traditional mind maps.

Another limitation pertains to the fixed task durations. While the study provided set times for each task, these durations may not accurately reflect the actual time needed for participants to fully engage with and comprehend the mind maps, especially for more complex video content. Flexible task durations that align with the complexity of the videos could yield more accurate measures of time and effort required for both AI-generated and human-generated mind maps.

Additionally, the AI tool used for generating mind maps in this study may have unique limitations that are not representative of all AI models and algorithms. The specific capabilities and constraints of this tool could influence the outcomes, suggesting the need for future studies to consider multiple AI models and algorithms. Furthermore, the study did not explore a wide range of prompts. The quality and structure of prompts can significantly affect the output of AI-generated mind maps. By not experimenting with various prompts, we may have overlooked potential variations in effectiveness and quality.

It is also important to note that designers are a niche group of individuals who are particularly accustomed to incorporating multiple tools into their workflow. Consequently, their adoption rate of new tools is higher, and they can adjust more easily to new interventions. This characteristic should be considered when comprehending the workflow for other applications and use cases, as the ease of adoption observed in designers may not directly translate to other professions or contexts.

6.4. Future Work

Looking ahead, future research should aim to address these limitations and expand on the insights gained from this study. Increasing the sample size and ensuring a more diverse group of participants would enhance the reliability and generalizability of the findings. This broader participant base would allow for a more detailed understanding of how different demographics and user backgrounds impact the effectiveness of AI-generated and tradi-tional mind maps.

Moreover, future research should explore the mind-mapping workflow more comprehen-sively. After implementing the suggested improvements, it would be beneficial to test the mind-mapping tool by having designers perform video-based design activities with and without the aid of the tool. This study primarily compared LLM-generated mind maps with those created by humans but did not examine the impact of incorporating the mind map tool into the workflow. Understanding how the mind map aids in creativity, brainstorming, and deriving insights requires a different setup of study and activities. Such an investigation would provide deeper insights into the tool's effectiveness in enhancing the quality of in-sights and supporting the designer's creative process.

Additionally, the subjective nature of the context and the type of video content for which the mind maps are generated should be studied further. This study does not provide significant contributions to the effect of context on the mind map or its possible applications. Devel-oping a framework or set of guidelines to determine which cases and applications this tool works best would be invaluable. This framework could help identify the specific scenarios where AI-generated mind maps offer the most benefit and ensure their optimal use in vari-ous contexts.

Exploring different AI models and algorithms remains crucial. By testing a variety of AI tech-nologies with diverse capabilities, future studies can provide a more comprehensive un-derstanding of the potential and limitations of AI-generated mind maps. Future studies should consider the evolving capabilities of these models and their impact on the quality and usability of AI-generated mind maps. Furthermore, the study should explore a wider range of prompts. The quality and structure of prompts can significantly affect the output of AI-generated mind maps. Experimenting with various prompts will help uncover the best practices for maximizing the effectiveness and accuracy of AI-generated content.

Conducting longitudinal studies could further enrich our understanding of the long-term benefits and challenges associated with AI-generated mind maps. Longitudinal studies in-volve tracking participants' interactions with the tool over an extended period, allowing re-searchers to observe how users adapt to and integrate AI-generated mind maps into their workflows over time. This approach provides valuable insights into the sustained usability, learning curves, and potential improvements in efficiency and effectiveness that may not be evident in short-term studies.

6.5. Conclusion

In conclusion, this research rigorously evaluates the integration of AI-generated mind maps into the video-based design (VBD) process, demonstrating notable impacts on efficiency and cognitive load. The designed plugin leverages Large Language Models (LLMs) to generate mind maps that summarize video content, thus providing designers with a quick and structured overview. This study involved 28 design practitioners who engaged with the plugin in a series of tasks, revealing that the AI-generated mind maps effectively reduced video analysis time and provided a good starting point for further design work. However, the plugin's current iteration also exhibited significant drawbacks, such as poor organization, lack of hierarchical structure, and cluttered presentations, which necessitated further human adjustments to be truly effective.

The comparative analysis between human-generated and AI-generated mind maps underscored several qualitative differences. Human mind maps were found to be more reliable in terms of organization, contextual understanding, and critical thinking. On the other hand, AI-generated mind maps excelled in efficiency and objectivity but often lacked clarity and detailed accuracy. Participants indicated a preference for human-generated mind maps due to their structured approach and nuanced insights, though they acknowledged the AI's utility in quickly capturing relevant information and reducing initial cognitive load.

Looking ahead, the potential for AI in the design process is substantial. The findings suggest that with continued refinement, particularly in improving the structure and reliability of outputs and enhancing the user interface, AI-generated mind maps can become an indispensable tool for designers. By incorporating user feedback and advancing the technology, the balance between human creativity and AI efficiency can be optimized. This integration holds promise for significantly augmenting the VBD process, enabling designers to focus more on creative and strategic aspects while relying on AI to handle more routine and time-consuming tasks.

However, it is essential to exercise caution and balance in leveraging AI tools. As illustrated by the Tamil proverb *"Azhavai minjinal amudhamum keduthu" — even nectar becomes poison if consumed in excess* — the study highlights the importance of proper use and moderation. Over-reliance on AI can lead to dependency, overshadowing the human element critical to nuanced and creative design thinking. Just as excessive reliance on AI-generated mind maps can result in the loss of critical human insight and contextual understanding, it is vital to strike a balance, integrating AI as a valuable assistant rather than a replacement. By maintaining this balance, we can ensure that AI tools enhance rather than detract from the creative and analytical processes essential to effective design. Ultimately, it is the blend of human ingenuity and AI efficiency that will drive forward the future of design, allowing both elements to complement and elevate each other.

References

- Abdellahi, S., Maher, M. L., Siddiqui, S., Rezwana, J., & Almadan, A. (2020). Arny: a study of a co-creative interaction model focused on emotion feedback. In Lecture notes in computer science (pp. 377–396). https://doi.org/10.1007/978-3-030-60117-1_28.
- Agustianto, K., Utomo, A. H., Ayuninghemi, R., Destarianto, P., Wiryawan, I. G., & Mulyadi, E. (2022). Eye tracking usability testing using User-Centered Design Analysis Method. Advances in Social Science, Education and Humanities Research/Advances in Social Science, Education and Humanities Research. https://doi.org/10.2991/assehr.k.220207.045.
- Agustianto, R., Widodo, A., & Purwanto, B. (2022). Analysis of user interaction with digital interfaces using eye-tracking metrics. International Journal of Human-Computer Interaction, 38(2), 211-225.
- AI generated Mind Maps | Collaborative AI Mind Mapping Tool | Creately. (2024, July 25). AI generated Mind Maps | Collaborative AI Mind Mapping Tool | Creately. https://creately.com/lp/viz/ai-mindmap/
- Alrefaei, D., Zhang, L., Sankar, G., Djamasbi, S., Tulu, B., Flanagan, C., Kalayjian, A., Ge, C., Franco, C., Meraj, S., & Muehlschlegel, S. (2023). Using Eye Tracking to Measure User Engagement with a Decision Aid. In Lecture notes in computer science (pp. 57–70). https://doi.org/10.1007/978-3-031-35017-7_5.
- Alrefaei, Y., Jiang, Y., & Redmill, D. (2023). Eye-tracking in UX research: Comprehensive insights for design improvements. Journal of User Experience, 12(1), 45-62.
- Anggy, Ayu, Maharrany., Tukiran., Sunu, Kuntjoro. (2022). Mind mapping promotes the application of flipped classroom teaching model in the teaching of inorganic chemical elements compounds.
- AprilTag. (n.d.). https://april.eecs.umich.edu/software/apriltag
- Awanto, A. N., Ardianto, Y. T., & Prasetya, D. A. (2020). UTAUT Model implementation on user behavior in use of Information Technology. Jurnal Teknologi Dan Manajemen Informatika/Jurnal Teknologi Dan Manajemen Informatika, 6(1). https://doi.org/10.26905/jtmi.v6i1.4156.
- Awanto, D., Tarigan, J., & Santoso, B. (2020). Social influence on technology adoption. Journal of Educational Technology Research, 18(3), 45-62.
- Ayre, J.. (2022). Research Note: Thematic analysis in qualitative research. 68(1). https://doi.org/10.1016/j.jphys.2021.11.002 Beatty, J. (1982). Task-evoked pupillary responses, processing load, and the structure of processing resources. Psychological Bulletin, 91(2), 276-292.
- Bansal, G., Smith-Renner, A. M., Buçinca, Z., Wu, T., Holstein, K., Hullman, J., & Stumpf, S. (2022). Workshop on Trust and Reliance in AI-Human Teams (TRAIT). CHI Conference on Human Factors in Computing Systems Extended Abstracts. https://doi.org/10.1145/3491101.3503704.
- Beel, J., & Langer, S.. (2011). An exploratory analysis of mind maps. https://doi.org/10.1145/2034691.2034709.
- Belina, A. (2023). Semi-structured interviewing as a tool for understanding informal civil society. Voluntary Sector Review, 14(2), 331–347. https://doi.org/10.1332/204080522x16454629995872.
- Blumer, H. (1986). The Methodological Position of Symbolic Interactionism. In Symbolic Interactionism: Perspective and Method. University of California Press.
- Blumer, H., & Shepherd, C. R.. (1970). Symbolic Interactionism: Perspective and Method. 48(3). https://doi.org/10.2307/2574696.
- Bo, C.. (2017). Mind map display method and device (Patent).
- Boşnak, B. (2022). SEMI-STRUCTURED INTERVIEWS IN CIVIL SOCIETY STUDIES: NOTES FROM THE FIELD. Pamukkale ÜNiversitesi Sosyal Bilimler EnstitüSü Dergisi. https://doi.org/10.30794/pausbed.1116964.
- Buschek, D., Mecke, L., Lehmann, F., & Dang, H. (2021). Nine Potential Pitfalls when Designing Human-AI Co-Creative Systems. arXiv (Cornell University). http://arxiv.org/abs/2104.00358.
- Buzan, T. (2006). The Mind Map Book: Unlock Your Creativity, Boost Your Memory, Change Your Life. BBC Active.
- Capel, T., & Brereton, M. (2023). What is Human-Centered about Human-Centered AI? A Map of the Research Landscape. Association for Computing Machinery. https://doi.org/10.1145/3544548.3580959.
- Canas, A. J., Hill, G., Carff, R., Suri, N., Lott, J., Gómez, G., ... & Carvajal, R. (2005). CmapTools: A knowledge

modeling and sharing environment. Concept maps: theory, methodology, technology, 1, 125-133.

» Cao, A., Chintamani, K. K., Pandya, A. K., & Ellis, R. D. (2009). NASA TLX: Software for assessing subjective mental workload. Behavior Research Methods, 41(1), 113–117. https://doi.org/10.3758/brm.41.1.113.
» Cao, Y., Ishihara, Y., & Takano, S. (2009). Detailed diagnostic workload analysis with NASA-TLX. Ergonomics Journal, 12(1), 15-27.
» Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2021). Adoption of AI-integrated systems. International Journal of Information Management, 56, 102098.
» Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing Organizational Users' Intentions and Behavior to AI Integrated CRM Systems: a Meta-UTAUT Approach. Information Systems Frontiers, 25(4), 1299–1313. https://doi.org/10.1007/s10796-021-10181-1.
» Chen, Tialong. (2020). Mind Map Displaying Method and Device, Apparatus, and Storage Medium
» Chen, F. F., Zhao, H., Zhang, Q., Shi, J., Xu, S., & Xu, B.. (2023). X-LLM: Bootstrapping Advanced Large Language Models by Treating Multi-Modalities as Foreign Languages. abs/2305.04160. https://doi.org/10.48550/arXiv.2305.04160.
» Chen, G., Zheng, Y.-D., Wang, J., Xu, J., Huang, Y., Pan, J., Wang, Y., Wang, Y., Qiao, Y., Lu, T., & Wang, L.. (2023). VideoLLM: Modeling Video Sequence with Large Language Models. abs/2305.13292. https://doi.org/10.48550/arXiv.2305.13292.
» Chen, Z., Qing, J., & Zhou, J.. (2023). Cinematic Mindscapes: High-quality Video Reconstruction from Brain Activity. abs/2305.11675. https://doi.org/10.48550/arXiv.2305.11675.
» D'Antoni, A. V., Zipp, G. P., & Olson, V. G. (2009). Interrater reliability of the mind map assessment rubric in a cohort of medical students. BMC Medical Education, 9(1). https://doi.org/10.1186/1472-6920-9-19.
» Davies, M. (2011). Concept mapping, mind mapping and argument mapping: What are the differences and do they matter? Higher Education, 62(3), 279-301.
» De Blanes Sebastián, J., Luján-Mora, S., & Ivorra-Piqueres, F. (2022). User acceptance in AI-integrated systems. AI & Society, 37, 685-700.
» De Blanes Sebastián, M. G., Guede, J. R. S., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.993935.
» Duchowski, A. T. (2007). Eye tracking methodology: Theory and practice. Springer.
» EdrawMind AI - AI-Powered Mind Mapping Made Simple and Intuitive. (2024, July 25). EdrawMind AI - AI-Powered Mind Mapping Made Simple and Intuitive. https://www.edrawmind.com/ai-mind-map.html
» eLearning Industry (2024, July 24). Is It Really A Battle Of The Brains? AI Versus Human Intelligence. https://elearningindustry.com/is-it-really-a-battle-of-the-brains-ai-versus-human-intelligence
» Eppler, M. J. (2006). A comparison between concept maps, mind maps, conceptual diagrams, and visual metaphors as complementary tools for knowledge construction and sharing. Information Visualization, 5(3), 202-210.
» Fotler, D., Germann, R., Gröbe-Boxdorfer, B., Engeln, W., & Matthiesen, S. (2021). User-Centered Design – evolution of an interdisciplinary process approach utilizing empirical research methods. In Lecture notes in networks and systems (pp. 431–442). https://doi.org/10.1007/978-3-030-85540-6_56.
» Gaole, H., L.H., K., & Gadiraju, U.. (2023). Knowing About Knowing: An Illusion of Human Competence Can Hinder Appropriate Reliance on AI Systems. https://doi.org/10.1145/3544548.3581025.
» Gmeiner, F., Holstein, K. A., & Martelaro, N.. (2022). Team Learning as a Lens for Designing Human-AI Co-Creative Systems. abs/2207.02996. https://doi.org/10.48550/arXiv.2207.02996.
» Guo, Q.. (2021). Research on the Application of Mind Map in Multimedia Network Teaching Environment. 1827(1). https://doi.org/10.1088/1742-6596/1827/1/012162.
» Hagendorff, T., & Fabi, S.. (2022). Methodological reflections for AI alignment research using human feedback. abs/2301.06859. https://doi.org/10.48550/arXiv.2301.06859.
» Hart, S. G. (2006). NASA-task load index (NASA-TLX); 20 years later. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 50(9), 904-908.

- Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in Psychology, 52, 139-183.
- Hua, C., & Wind, S. A. (2018). Exploring the psychometric properties of the mind-map scoring rubric. Behaviormetrika, 46(1), 73–99. https://doi.org/10.1007/s41237-018-0062-z.
- Hua, J., & Wind, S. A. (2018). Enhancing the assessment of mind maps: Reliability, validity, and holistic scoring. Educational Technology Research and Development, 66(4), 1039-1056.
- Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). Eye tracking: A comprehensive guide to methods and measures. Oxford University Press.
- Jian, J., Lee, J., & Kim, S. (2022). Quantifying user satisfaction in automotive interfaces through eye movement analysis. Automotive UX Journal, 5(3), 201-218.
- Jian, M., Bo, Z., & Ya'nan, L. (2022). Research on user experience evaluation method based on eye movement technology. 2022 6th CAA International Conference on Vehicular Control and Intelligence (CVCI). https://doi.org/10.1109/cvci56766.2022.9964563.
- Jung, H., Lee, S., & Kim, J. (2021). Remote eye-tracking studies: Behavioral data collection in the absence of physical presence. Behavioral Research Methods, 53(4), 1002-1015.
- Jung, S., Salminen, J., & Jansen, B. (2021). Implementing Eye-Tracking for persona Analytics. ACM Symposium on Eye Tracking Research and Applications. https://doi.org/10.1145/3450341.3458765.
- Kadagidze, L.. (2016). Mind Mapping as a Teaching Tool in Higher Education Language Learning Settings. 114(4). https://doi.org/10.15804/KIE.2016.04.05.
- Karamolegkou, A., Abdou, M., & Søgaard, A. (2023). Mapping Brains with Language Models: A Survey. arXiv. https://doi.org/10.18653/v1/2023.findings-acl.618.
- Karthik, V., Sreedharan, S., Marquez, M., Hernandez, A. O., & Kambhampati, S.. (2023). On the Planning Abilities of Large Language Models (A Critical Investigation with a Proposed Benchmark). abs/2302.06706. https://doi.org/10.48550/arXiv.2302.06706.
- Keinonen, T., & Takala, R.. (2006). Product Concept Design. Springer London. https://doi.org/10.1007/978-1-84628-126-6
- Khechine, H., Lakhal, S., & Ndjambou, P. (2016). A metaanalysis of the UTAUT model: Eleven years later. Canadian Journal of the Administrative Sciences/Canadian Journal of Administrative Sciences, 33(2), 138–152. https://doi.org/10.1002/cjas.1381.
- Khechine, H., Lakhal, S., Pascot, D., & Bytha, A. (2016). UTAUT model for blended learning: The role of gender and age in the intention to use webinars. Interdisciplinary Journal of E-Learning and Learning Objects, 12(1), 101-117.
- Khechine, H., Lakhal, S., Pascot, D., & Bytha, A. (2016). UTAUT2 model in technology adoption. Journal of Technology Research, 8, 22-43.
- Kim, J., & Maher, M. L. (2023). The effect of AI-based inspiration on human design ideation. International Journal of Design Creativity and Innovation, 11(2), 81–98. https://doi.org/10.1080/21650349.2023.2167124.
- Kitap, Tez, Sempozyum Değerlendirmeleri / John Dewey, How We Think, A Restatement of The Relation of Reflective Thinking to The Educative Process, D. C. Heath and Company, 1933, 10+301 s.. (1933, June 26).
- Kraft, C.. (2012). User Experience Innovation: User Centered Design that Works.
- Krippendorff, K., & Wester, F. P. J.. (2005). Content analysis. An introduction to its methodology. 30.
- Kułak, J. P., Trojanowski, M., & Barmentloo, E. (2019). A Literature Review of the Partial Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. Annales Universitatis Mariae Curie-Skłodowska. Sectio H, Oeconomia, 53(4), 101. https://doi.org/10.17951/h.2019.53.4.101-113.
- Kułak, K., Dąbrowski, W., & Stępień, M. (2019). Predictors of AI adoption. Technology Adoption Quarterly, 23(2), 77-88.
- Kvale, S. (2008). Doing Interviews. SAGE.
- Larsson, T., Font, J., & Alvarez, A. (2022). Towards AI as a creative colleague in game level design.

Proceedings, 18(1), 137–145. https://doi.org/10.1609/aiide.v18i1.21957.
» Leiker, D., & Cukurova, M.. (2023). Prototyping the use of Large Language Models (LLMs) for adult learning content creation at scale. abs/2306.01815. https://doi.org/10.48550/arXiv.2306.01815.
» Li, M., Zhao, Y., Yu, B., Song, F., Li, H., Yu, H., Li, Z., Huang, F., & Li, Y. (2023). API-Bank: A Comprehensive Benchmark for Tool-Augmented LLMs. arXiv. https://doi.org/10.18653/v1/2023.emnlp-main.187.
» Ma, C., Liu, Y.-J., Zhao, G., & Wang, H.. (2016). Visualizing and Analyzing Video Content With Interactive Scalable Maps. 18(11). https://doi.org/10.1109/TMM.2016.2614229.
» Maher, M. L. & Rezwana, J.. (2022). Designing Creative AI Partners with COFI: A Framework for Modeling Interaction in Human-AI Co-Creative Systems. https://doi.org/10.1145/3519026.
» McKendrick, R., & Cherry, C. (2018). NASA-TLX in usability testing. Journal of Human Factors, 60(1), 22-32.
» McKendrick, R. D., & Cherry, E. (2018). A deeper look at the NASA TLX and where it falls short. Proceedings of the Human Factors and Ergonomics Society Annual Meeting/Proceedings of the Human Factors and Ergonomics Society . . . Annual Meeting, 62(1), 44–48. https://doi.org/10.1177/1541931218621010.
» Mozannar, H., Bansal, G., Fourney, A., & Horvitz, E.. (2022). Reading Between the Lines: Modeling User Behavior and Costs in AI-Assisted Programming. abs/2210.14306. https://doi.org/10.48550/arXiv.2210.14306.
» Mozannar, H., Sculley, D., & Norvig, P. (2022). Improving AI system performance through workload assessment. AI Performance Review, 10(2), 155-173.
» Muradoglu, M., Cimpian, J. R., & Cimpian, A.. (2023). Mixed-Effects Models for Cognitive Development Researchers. 24(3). https://doi.org/10.1080/15248372.2023.2176856
» NASA-TLX Web App: An Online Tool to Analyse Subjective Workload. (2020, January 27). NASA-TLX Web App: An Online Tool to Analyse Subjective Workload.
» Negalur, B., Vaddatti, T., Kiran, P. R., Renuka, I., Laxmi, K., & Potti, R.. (2022). The effectiveness of mind mapping as a learning strategy in promoting information retrieval among II MBBS students. 10(1). https://doi.org/10.4103/amhs.amhs_120_21.
» Ngoc, T.. (2023). The Use of Mind-Mapping Technique towards Students' English Vocabulary Retention at a Primary School. 06(05). https://doi.org/10.47191/ijsshr/v6-i5-64.
» Notion AI | Now with Q&A. (2024, July 25). Notion AI | Now with Q&A. https://www.notion.so/product/ai
» Novak, J. D., & Canas, A. J. (2008). The theory underlying concept maps and how to construct and use them. Florida Institute for Human and Machine Cognition Pensacola FL, 1(1), 1-31.
» Noyes, J., & Cook, M.. (2012). User-Centred Design of Systems.
» OpenAI, Achiam, Josh, Adler, Steven, etc. (2023). GPT-4 Technical Report. abs/2303.08774. https://doi.org/10.48550/arXiv.2303.08774
» Or, C. (2023). Revisiting unified theory of technology and use of technology using meta-analytic structural equation modelling. International Journal of Technology in Education and Science, 7(1), 83–103. https://doi.org/10.46328/ijtes.420.
» Or, C. (2023). Factors influencing acceptance and use of cloud-based electronic health records. Health Informatics Journal, 29(1), 14604582221085077.
» Or, C. K. L. (2023). Mixed results in facilitating conditions. Technology Use Journal, 19(3), 45-60.
» Palaniappan, V., Karthikeyan, K., & Mohan, R.. (2023). Mind Mapping as a Novel Method in Teaching the Morphology of Skin Lesions: A Quasi-Experimental Study. 11. https://doi.org/10.30476/JAMP.2023.97240.1750.
» Pan, S., Luo, L., Wang, Y., Chen, C., Wang, J., & Wu, X.. (2023). Unifying Large Language Models and Knowledge Graphs: A Roadmap. abs/2306.08302. https://doi.org/10.48550/arXiv.2306.08302.
» Poole, A., & Ball, L. J. (2006). Eye tracking in HCI and usability research. In Encyclopedia of Human-Computer Interaction (pp. 211-219). IGI Global.
» Puchert, P., Arora Poonam, P., van Onzenoodt, C., & Ropinski, T.. (2023). LLMMaps - A Visual Metaphor for Stratified Evaluation of Large Language Models. abs/2304.00457. https://doi.org/10.48550/

arXiv.2304.00457.
» Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. Psychological Bulletin, 124(3), 372-422.
» Rezwana, J., & Maher, M. L. (2022). Understanding user perceptions, collaborative experience and user engagement in different Human-AI interaction designs for Co-Creative systems. Creativity and Cognition. https://doi.org/10.1145/3527927.3532789.
» Rezwana, J., & Maher, M. L.. (2022). Identifying Ethical Issues in AI Partners in Human-AI Co-Creation. abs/2204.07644. https://doi.org/10.48550/arXiv.2204.07644.
» Rezwana, J., & Maher, M. L. (2023). User Perspectives on Ethical Challenges in Human-AI Co-Creativity: A Design Fiction study. Creativity and Cognition. https://doi.org/10.1145/3591196.3593364.
» Rubio, S., Diaz, E., Martin, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Ergonomics, 35(1), 61-67.
» Salmon, P. M., Baber, C., Burns, C., Carden, T., Cooke, N., Cummings, M., Hancock, P., McLean, S., Read, G. J. M., & Stanton, N. A. (2023). Managing the risks of artificial general intelligence: A human factors and ergonomics perspective. Human Factors and Ergonomics in Manufacturing & Service Industries/Human Factors and Ergonomics in Manufacturing, 33(5), 366–378. https://doi.org/10.1002/hfm.20996.
» Sbaa, M., Faouzi, L., Eljahechi, M., & Lghdaich, F.. (2022). The Mind Map at the Service of Learning. 05. https://doi.org/10.47191/ijmra/v5-i12-37.
» Scharowski, N., Perrig, S., von Felten, N., & Brühlmann, F.. (2022). Trust and Reliance in XAI - Distinguishing Between Attitudinal and Behavioral Measures. abs/2203.12318. https://doi.org/10.48550/arXiv.2203.12318.
» Schoen, D.. (1983). The reflective practitioner.
» Schoenherr, J. R., Abbas, R., Michael, K., Rivas, P., & Anderson, T. D. (2023). Designing AI using a Human-Centered approach: Explainability and accuracy toward trustworthiness. IEEE Transactions on Technology and Society, 4(1), 9–23. https://doi.org/10.1109/tts.2023.3257627.
» Shi, Y., Shi, Y., Ma, L., Ma, L., & Liu, L.. (2020). Mixed Effects Envelope Models. 9(1). https://doi.org/10.1002/STA4.313
» Siochos, V., & Papatheodorou, C. (2011). Developing a Formal Model for Mind Maps. Database & Information System Group, Laboratory of Digital Libraries and Electronic Publications, Department of Archives and Library Sciences, Ionian University, Corfu, Greece.
» Springer, J. D., & Kyas, M.. (2022). Evaluation of April Tag and WhyCode Fiducial Systems for Autonomous Precision Drone Landing with a Gimbal-Mounted Camera. abs/2203.10180. https://doi.org/10.48550/arXiv.2203.10180
» Stern, J. A., Boyer, D., & Schroeder, D. (1994). Blink rate: A possible measure of fatigue. Human Factors, 36(2), 285-297.
» Stone, T., & Chapman, C. (2023). Identifying usability issues in menu navigation tasks using eye-tracking technology. Journal of Usability Studies, 18(2), 112-130.
» Stone, S. A., & Chapman, C. S. (2023). Unconscious Frustration: Dynamically Assessing User Experience using Eye and Mouse Tracking. Proceedings of the ACM on Human-computer Interaction, 7(ETRA), 1–17. https://doi.org/10.1145/3591137.
» Storyful News & Weather. (2020, July 28). Visually impaired woman demonstrates how she uses her iPhone [Video]. YouTube. https://www.youtube.com/watch?v=EEpsoCPL518
» Tomas, C., Whitt, E., Lavelle-Hill, R., & Severn, K. (2019). Modeling holistic marks with analytic rubrics. Frontiers in Education, 4. https://doi.org/10.3389/feduc.2019.00089.
» Vasconcelos, H., Jörke, M., Grunde-McLaughlin, M., Gerstenberg, T., Bernstein, M. S., & Krishna, R. (2023). Explanations can reduce overreliance on AI systems during Decision-Making. Proceedings of the ACM on Human-computer Interaction, 7(CSCW1), 1–38. https://doi.org/10.1145/3579605.
» Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178.
» Vimalaksha, A., Vinay, S., & Kumar, N. S. (n.d.). Hierarchical Mind Map Generation from Video Lectures.

Computer Science, Education. https://doi.org/10.1109/t4e.2019.00-40.

» Watson, M. K., Pelkey, J., Noyes, C. R., & Rodgers, M. O. (2015). Assessing conceptual knowledge using three concept map scoring methods. Journal of Engineering Education, 105(1), 118–146. https://doi.org/10.1002/jee.20111.

» Wang, Xu., Guo, Xiaoli. (2019). A mind map display method and device.

» Wu, C. (2022). Application of eye movement tracking technology in web design. Frontiers in Computing and Intelligent Systems, 2(2), 16–18. https://doi.org/10.54097/fcis.v2i2.3740.

» Wu, Y. (2022). Enhancing UX design with eye-tracking: Patterns, issues, and insights. Human-Computer Interaction Review, 29(1), 87-103.

» Xmind - Full-featured mind mapping and brainstorming tool. (2024, July 25). Xmind - Full-featured mind mapping and brainstorming tool. https://xmind.app

» Xu, W.. (2022). User-Centered Design (VIII): A New Framework of Intelligent Sociotechnical Systems and Research Prospects. abs/2201.05980.

» Yang, G., Ma, C., & Wang, H.. (2016). VideoMap: An interactive and scalable visualization for exploring video content. 2(3). https://doi.org/10.1007/S41095-016-0049-1

» Yax, N., Anlló, H., & Palminteri, S. (2024). Studying and improving reasoning in humans and machines. Communications Psychology, 2(1). https://doi.org/10.1038/s44271-024-00091-8.

» Yu, L., Cheng, Y., Wang, Z., Kumar, V., Macherey, W., Huang, Y., Ross, D. A., Essa, I., Bisk, Y., Yang, M.-X., Murphy, K., Hauptmann, A. G., & Jiang, L.. (2023). SPAE: Semantic Pyramid AutoEncoder for Multimodal Generation with Frozen LLMs. abs/2306.17842. https://doi.org/10.48550/arXiv.2306.17842.

» Yune, S. J., Lee, S. Y., Im, S. J., Kam, B. S., & Baek, S. Y. (2018). Holistic rubric vs. analytic rubric for measuring clinical performance levels in medical students. BMC Medical Education, 18(1). https://doi.org/10.1186/s12909-018-1228-9.

» Zhang, W. (2020). A study on the user acceptance model of artificial intelligence music based on UTAUT. Journal of the Korea Society of Computer and Information, 25(6), 25–33. https://doi.org/10.9708/JKSCI.2020.25.06.025.

» Zhang, P. (2020). Performance expectancy in AI adoption. Journal of Information Technology, 35(4), 1021-1039.

» Zhao, Z., Song, S., Duah, B., Macbeth, J., Carter, S., Van, M. P., Bravo, N. S., Klenk, M., Sick, K., & Filipowicz, A. L. S. (2023). More human than human: LLM-generated narratives outperform human-LLM interleaved narratives. Creativity and Cognition. https://doi.org/10.1145/3591196.3596612.

» Zhu, H., Axon, A., Bertsch, A., Deng, W., Ding, Z., Guo, B. B., Gururaja, S., Kuo, T.-S., Liang, J., Milbauer, J., Padmanabhan, N. K. A., Wu, Z., & Yang, C.. (2023). LLMs as Workers in Human-Computational Algorithms? Replicating Crowdsourcing Pipelines with LLMs.

» Zhuang, Y., Li, Q., Ning, Y., Huang, W., Lv, R., Huang, Z., Zhang, Z., Mao, Q., Wang, S., & Chen, E.. (2023). Efficiently Measuring the Cognitive Ability of LLMs: An Adaptive Testing Perspective. abs/2306.10512. https://doi.org/10.48550/arXiv.2306.10512.

» Zhou, L., Rudin, C., Gombolay, M., Spohrer, J., Zhou, M., & Paul, S. (2023). From artificial intelligence (AI) to intelligence augmentation (IA): design principles, potential risks, and emerging issues. AIS Transactions on Human-computer Interaction, 15(1), 111–135. https://doi.org/10.17705/1thci.00085.

» Zuo, Y., & Gu, Y. (2022). Mind mapping promotes the application of flipped classroom teaching model in the teaching of inorganic chemical elements compounds. Journal of Education and Practice. https://doi.org/10.7176/jep/13-30-15.

» Zvauya, R., Purandare, S., Young, N., & Pallan, M. (2017). The use of mind maps as an assessment tool in a problem based learning course. Creative Education, 08(11), 1782–1793. https://doi.org/10.4236/ce.2017.811122.

»

Appendix

UTAUT 2 QUESTIONNAIRE

Performance Expectancy:

I believe that using the AI-generated mind map tool will improve my video-based design workflow.
I expect the mind map tool to enhance my overall productivity.
I perceive the mind map tool as a valuable addition to my design work.
Effort Expectancy:

Interacting with the mind map tool is straightforward and understandable.
It would be easy for me to become skillful at using the mind map tool.
Hedonic Motivation:

The mind map tool adds interest to my design process.
Social Influence:

I am more likely to use the AI-generated mind map tool if I see other design professionals using it.
The opinions of other designers significantly influence my intention to adopt the AI-generated mind map tool.
Facilitating Conditions:

I feel confident in my ability to use the mind map tool due to the available resources and assistance.
Behavioral Intention:

I intend to continue using the mind map tool for video-based design.
I would frequently incorporate the mind map tool into my video-based design routine.
I am likely to recommend the mind map tool to others in my field.
Habit:

Using the mind map tool has become a habit for me.
Price Value:
Considering the effort required, the mind map tool provides good value.

PROMPTS

Prompt 1:
You are a data expert who can combine the sentences from a dataset with transcripts into a paragraph as whole description. Please generate one descriptive paragraph and focus on the contents of the sentences, not the other information such as video title or frames. Omit receptive sentences from the data and extract the useful information to integrate as a paragraph. Obtain all details from the input. Output the paragraph only. Here is the dataset: "...". Here is the transcript: "...".

Prompt 2:
Output a json as plain text to describe the scenario. The JSON should contains nodes whose "label" are related keywords from the topic and edges with "label" as relationships. Include unique ID, position, size, shape for nodes; source, target for edges; and styles for both, with edge length reflecting semantic relevance. Do not put the same IDs for edges. Depend on the contents, generate more than 20 but not less than 30 nodes and edges, and generate 1 to 3 levels of branches as subtopics. Use different node and edge color and edge length to represent relationships. Avoid overlapping. Focus on objective interactions. This is an example: "{
 "nodes": [
  {"id": "Node1", "x": 50, "y": 50, "size": [60, 60], "shape": "circle", "label": "Apple"},

{“id”: “Node2”, “x”: 200, “y”: 50, “size”: [60, 60], “shape”: “circle”, “label”: “iOS”},
{“id”: “Node3”, “x”: 350, “y”: 50, “size”: [60, 60], “shape”: “circle”, “label”: “App Store”},
{“id”: “Node4”, “x”: 500, “y”: 50, “size”: [60, 60], “shape”: “circle”, “label”: “Face ID”},
{“id”: “Node5”, “x”: 650, “y”: 50, “size”: [60, 60], “shape”: “circle”, “label”: “Siri”},
{“id”: “Node6”, “x”: 50, “y”: 250, “size”: [60, 60], “shape”: “circle”, “label”: “iCloud”},
{“id”: “Node7”, “x”: 200, “y”: 250, “size”: [60, 60], “shape”: “circle”, “label”: “A-Series Chip”},
{“id”: “Node8”, “x”: 350, “y”: 250, “size”: [60, 60], “shape”: “circle”, “label”: “Retina Display”},
{“id”: “Node9”, “x”: 500, “y”: 250, “size”: [60, 60], “shape”: “circle”, “label”: “Touch ID”},
...
{“id”: “Node25”, “x”: 650, “y”: 250, “size”: [60, 60], “shape”: “circle”, “label”: “Lightning Connector”}
],
“edges”: [
{“source”: “Node1”, “target”: “Node2”, “label”: “operates”},
{“source”: “Node1”, “target”: “Node3”, “label”: “hosts”},
{“source”: “Node2”, “target”: “Node4”, “label”: “supports”},
{“source”: “Node2”, “target”: “Node5”, “label”: “integrates”},
{“source”: “Node1”, “target”: “Node6”, “label”: “provides”},
{“source”: “Node1”, “target”: “Node7”, “label”: “contains”},
{“source”: “Node1”, “target”: “Node8”, “label”: “features”},
{“source”: “Node2”, “target”: “Node9”, “label”: “supported by”},
...
{“source”: “Node1”, “target”: “Node28”, “label”: “utilizes”}
]}”. Use the example as a template for generation but follow the rules above. This is the scenario: “...”. Here is the transcript: “...”.

Category	Fail (<48%)	Borderline (48% - 53%)	Average (54% - 64%)	Good (65% - 74%)	Very Good (75% - 100%)
Identification of triggers in the problem	Minimal or no identification of relevant concepts.	Limited identification of key concepts.	Some key concepts are identified, but there are gaps.	Key concepts are mostly identified but may lack some depth.	The mind map clearly identifies key concepts related to the problem.
Development of Valid Concept Links:	Minimal or no valid concept links.	Limited development of concept links.	Some concept links are developed, but additional exploration is needed.	Concept links are present but may lack depth or clarity.	The mind map demonstrates thorough exploration and development of concept links.
Development of Hierarchies:	No clear hierarchy.	Limited hierarchical organization.	Some attempt at hierarchy, but it lacks coherence.	Hierarchical arrangement is evident but may have minor inconsistencies.	Concepts are logically arranged in a hierarchical structure.
Identification of Cross Links and Relationship Links:	No evident cross links or relationship links.	Minimal meaningful connections.	Limited cross links and relationship links.	Some cross links and relationship links exist but may be sparse.	Meaningful connections between concepts (cross links) and within concepts (relationship links) are well-established.
Use of Colors and Pictures:	No use of colors or pictures.	Minimal visual enhancement.	Limited use of colors or pictures.	Some use of colors and pictures, but not consistently applied.	Colors and pictures enhance the mind map's visual appeal and clarity.

LMM

Dependent_Variable	Context_EM_Mean_1	Context_EM_Std_Error_1	Context_EM_Mean_2	Context_EM_Std_Error_2	Context_EM_P_Value	Context_EM_Significance	Who_Made_Map_EM_Mean_1	Who_Made_Map_EM_Std_Error_1	Who_Made_Map_EM_Mean_2	Who_Made_Map_EM_Std_Error_2	Who_Made_Map_EM_P_Value	Who_Made_Map_EM_Significance	Task_Number_EM_Mean_1	Task_Number_EM_Std_Error_1	Task_Number_EM_Mean_2	Task_Number_EM_Std_Error_2	Task_Number_EM_P_Value	Task_Number_EM_Significance	who_made_the_map_Context_P_Value	who_made_the_map_task_number_P_Value	Context_task_number_P_Value	who_made_the_map_Context_task_number_P_Value
PretaskTrigger	64.857	2.925	73.714	2.925	0.008	**Significant**	69.429	2.925	69.143	2.925	0.927	Not Significant	65.286	2.925	73.286	2.925	0.016	**Significant**	0.932	0.909	0.754	0.855
PretaskLink	63.286	3.519	64.714	3.519	0.708	Not Significant	64.929	3.519	63.071	3.519	0.627	Not Significant	60.750	3.519	67.250	3.519	0.098	Not Significant	0.981	0.695	0.934	0.259
PretaskHierarchy	53.286	4.371	59.643	4.371	0.144	Not Significant	62.143	4.371	50.786	4.371	0.012	**Significant**	60.536	4.371	52.393	4.371	0.065	Not Significant	0.111	0.912	0.185	0.289
PretaskRelation	55.857	4.634	59.679	4.634	0.428	Not Significant	55.679	4.634	59.857	4.634	0.387	Not Significant	55.786	4.634	59.750	4.634	0.411	Not Significant	0.073	0.124	0.390	0.363
TLX_Mental	58.571	3.795	58.750	3.795	0.965	Not Significant	56.786	3.795	60.536	3.795	0.356	Not Significant	65.000	3.795	52.321	3.795	0.004	**Significant**	0.206	0.226	0.935	0.825
TLX_Physical	20.536	4.857	25.536	4.857	0.095	Not Significant	24.107	4.857	21.964	4.857	0.463	Not Significant	22.321	4.857	23.750	4.857	0.623	Not Significant	0.033	0.621	0.569	1.000
TLX_Temporal	49.107	4.922	42.321	4.922	0.192	Not Significant	40.714	4.922	50.714	4.922	0.059	Not Significant	51.607	4.922	39.821	4.922	0.028	**Significant**	0.341	0.341	0.676	1.000
TLX_effort	43.571	4.399	43.036	4.399	0.910	Not Significant	39.464	4.399	47.143	4.399	0.116	Not Significant	46.250	4.399	40.357	4.399	0.223	Not Significant	0.092	0.794	0.905	0.910
TLX_Frustration	33.214	5.362	37.143	5.362	0.449	Not Significant	33.214	5.362	37.143	5.362	0.449	Not Significant	38.750	5.362	31.607	5.362	0.174	Not Significant	0.575	1.000	0.708	0.137
TLX_performance	48.071	4.033	56.286	4.033	0.010	**Significant**	53.321	4.033	51.036	4.033	0.444	Not Significant	50.893	4.033	53.464	4.033	0.390	Not Significant	0.243	0.449	0.100	0.117
TLX_Overall	42.179	2.928	43.845	2.928	0.523	Not Significant	41.267	2.928	44.757	2.928	0.187	Not Significant	45.804	2.928	40.220	2.928	0.040	**Significant**	0.475	0.795	0.600	0.433
UTAUT_PE	3.941	0.113	4.072	0.113	0.194	Not Significant	4.131	0.113	3.882	0.113	0.018	**Significant**	4.036	0.113	3.977	0.113	0.554	Not Significant	0.231	0.231	0.102	0.409
UTAUT_EE	3.696	0.144	3.821	0.144	0.254	Not Significant	3.875	0.144	3.643	0.144	0.040	**Significant**	3.661	0.144	3.857	0.144	0.079	Not Significant	0.740	0.643	0.266	0.869
UTAUT_SI	3.196	0.219	3.232	0.219	0.711	Not Significant	3.196	0.219	3.232	0.219	0.711	Not Significant	3.196	0.219	3.232	0.219	0.711	Not Significant	1.000	0.741	0.741	0.711
UTAUT_FC	3.786	0.169	3.607	0.169	0.272	Not Significant	3.750	0.169	3.643	0.169	0.507	Not Significant	3.786	0.169	3.607	0.169	0.272	Not Significant	0.906	0.019	0.200	0.272
UTAUT_BI	3.678	0.156	3.785	0.156	0.345	Not Significant	3.868	0.156	3.595	0.156	0.022	**Significant**	3.796	0.156	3.666	0.156	0.254	Not Significant	0.840	0.356	0.217	0.599
UTAUT_HM	3.571	0.179	3.964	0.179	0.110	Not Significant	3.714	0.179	3.821	0.179	0.657	Not Significant	3.786	0.179	3.750	0.179	0.882	Not Significant	0.894	0.150	0.150	0.657
UTAUT_PV	3.821	0.167	3.821	0.167	1.000	Not Significant	3.857	0.167	3.786	0.167	0.633	Not Significant	3.929	0.167	3.714	0.167	0.160	Not Significant	0.348	0.480	1.000	0.343
UTAUT_H	2.786	0.195	2.679	0.195	0.512	Not Significant	2.643	0.195	2.821	0.195	0.278	Not Significant	2.679	0.195	2.786	0.195	0.512	Not Significant	0.921	0.766	0.489	0.826
analyse_task_durationms	107941.488	12263.214	124315.793	12263.214	0.320	Not Significant	104168.222	12263.214	128089.059	12263.214	0.152	Not Significant	122478.642	12263.214	109778.640	12263.214	0.438	Not Significant	0.440	0.440	0.395	0.447
edit_task_durationms	382256.584	36394.626	389625.497	36394.626	0.875	Not Significant	328372.706	36394.626	443509.375	36394.626	0.020	**Significant**	445144.802	36394.626	326737.279	36394.626	0.017	**Significant**	0.919	0.593	0.375	0.170
blink_duration_in_analyse_taskms	275.028	9.245	281.661	9.245	0.251	Not Significant	279.805	9.245	276.884	9.245	0.609	Not Significant	283.198	9.245	273.492	9.245	0.098	Not Significant	0.290	0.149	0.870	0.409
blink_ct_in_analyse_task	23.429	5.314	32.857	5.314	0.178	Not Significant	27.571	5.314	28.714	5.314	0.868	Not Significant	31.893	5.314	24.393	5.314	0.280	Not Significant	0.904	0.369	0.789	0.568
blink_duration_in_edit_taskms	252.379	8.253	260.221	8.253	0.183	Not Significant	259.249	8.253	253.351	8.253	0.313	Not Significant	259.325	8.253	253.275	8.253	0.301	Not Significant	0.330	0.160	0.437	0.268
blink_ct_in_edit_task	82.893	13.747	81.679	13.747	0.940	Not Significant	71.250	13.747	93.321	13.747	0.177	Not Significant	97.000	13.747	67.571	13.747	0.076	Not Significant	0.431	0.165	0.681	0.114
saccade_duration_in_analysems	57.478	4.800	62.417	4.800	0.315	Not Significant	61.367	4.800	58.529	4.800	0.560	Not Significant	57.670	4.800	62.225	4.800	0.353	Not Significant	0.492	0.511	0.359	0.457
saccade_ct_in_analyse	245.250	28.116	270.500	28.116	0.501	Not Significant	242.464	28.116	273.286	28.116	0.413	Not Significant	267.143	28.116	248.607	28.116	0.621	Not Significant	0.604	0.573	0.198	0.392
saccade_duration_in_editms	60.380	3.621	59.150	3.621	0.515	Not Significant	60.958	3.621	58.572	3.621	0.212	Not Significant	60.648	3.621	58.883	3.621	0.353	Not Significant	0.226	0.372	0.455	0.543
saccade_ct_in_edit	899.571	84.296	913.786	84.296	0.895	Not Significant	770.714	84.296	1042.643	84.296	0.018	**Significant**	1037.821	84.296	775.536	84.296	0.022	**Significant**	0.295	0.278	0.314	0.087
saccade_amp_in_deg_analysedeg	5.013	0.269	5.217	0.269	0.497	Not Significant	5.113	0.269	5.117	0.269	0.989	Not Significant	4.927	0.269	5.303	0.269	0.214	Not Significant	0.424	0.773	0.288	0.438
saccade_amp_in_deg_editdeg	6.620	0.263	6.480	0.263	0.581	Not Significant	6.759	0.263	6.341	0.263	0.110	Not Significant	6.667	0.263	6.433	0.263	0.363	Not Significant	0.374	0.715	0.342	0.333
saccade_mean_velocity_in_analysepxs	1975.885	55.805	2009.083	55.805	0.550	Not Significant	2008.052	55.805	1976.916	55.805	0.575	Not Significant	1982.275	55.805	2002.693	55.805	0.713	Not Significant	0.345	0.123	0.618	0.381
saccade_mean_velocity_in_editpxs	2202.724	49.079	2180.559	49.079	0.561	Not Significant	2228.002	49.079	2155.281	49.079	0.065	Not Significant	2218.768	49.079	2164.515	49.079	0.162	Not Significant	0.824	0.047	0.482	0.148
pupil_diameter_left_analysemm	3.130	0.074	3.171	0.074	0.209	Not Significant	3.138	0.074	3.164	0.074	0.408	Not Significant	3.162	0.074	3.140	0.074	0.486	Not Significant	0.223	0.986	0.251	0.618
pupil_diameter_right_analysemm	3.109	0.079	3.153	0.079	0.163	Not Significant	3.117	0.079	3.145	0.079	0.363	Not Significant	3.140	0.079	3.122	0.079	0.552	Not Significant	0.217	0.953	0.392	0.647
pupil_diameter_left_editmm	3.130	0.074	3.171	0.074	0.209	Not Significant	3.138	0.074	3.164	0.074	0.408	Not Significant	3.162	0.074	3.140	0.074	0.486	Not Significant	0.223	0.986	0.251	0.618
pupil_diameter_right_editmm	3.109	0.079	3.153	0.079	0.163	Not Significant	3.117	0.079	3.145	0.079	0.363	Not Significant	3.140	0.079	3.122	0.079	0.552	Not Significant	0.217	0.953	0.392	0.647
fixation_duration_analysems	398.114	15.497	417.983	15.497	0.218	Not Significant	397.688	15.497	418.409	15.497	0.199	Not Significant	421.150	15.497	394.946	15.497	0.107	Not Significant	0.002	0.748	0.035	0.674
fixation_duration_editms	390.880	11.352	384.216	11.352	0.471	Not Significant	387.340	11.352	387.756	11.352	0.964	Not Significant	394.719	11.352	380.377	11.352	0.128	Not Significant	0.001	0.108	0.789	0.544
fixation_ct_analyse	232.929	25.430	247.000	25.430	0.701	Not Significant	220.893	25.430	259.036	25.430	0.303	Not Significant	245.250	25.430	234.679	25.430	0.773	Not Significant	0.595	0.663	0.148	0.282
fixation_ct_edit	782.786	78.870	791.857	78.870	0.929	Not Significant	645.857	78.870	928.786	78.870	0.010	**Significant**	889.429	78.870	685.214	78.870	0.055	Not Significant	0.283	0.207	0.217	0.201
Nr_of_nodes	25.393	0.708	26.179	0.708	0.414	Not Significant	25.964	0.708	25.607	0.708	0.708	Not Significant	29.179	0.708	22.393	0.708	<0.001	**Significant**	<0.001	0.194	0.429	<0.001
Nr_of_edges	27.643	0.881	27.786	0.881	0.891	Not Significant	28.143	0.881	27.286	0.881	0.415	Not Significant	30.357	0.881	25.071	0.881	<0.001	**Significant**	<0.001	0.283	0.622	<0.001
number_of_nodes_added	4.571	1.030	3.571	1.030	0.423	Not Significant	5.357	1.030	2.786	1.030	0.046	**Significant**	3.679	1.030	4.464	1.030	0.528	Not Significant	0.398	0.472	0.766	0.528
number_of_nodes_deleted	3.500	1.032	1.643	1.032	0.115	Not Significant	3.714	1.032	1.429	1.032	0.055	Not Significant	2.036	1.032	3.107	1.032	0.356	Not Significant	0.623	0.902	0.837	0.297

IDE Master Graduation Project

Project team, procedural checks and Personal Project Brief

In this document the agreements made between student and supervisory team about the student's IDE Master Graduation Project are set out. This document may also include involvement of an external client, however does not cover any legal matters student and client (might) agree upon. Next to that, this document facilitates the required procedural checks:

- Student defines the team, what the student is going to do/deliver and how that will come about
- Chair of the supervisory team signs, to formally approve the project's setup / Project brief
- SSC E&SA (Shared Service Centre, Education & Student Affairs) report on the student's registration and study progress
- IDE's Board of Examiners confirms the proposed supervisory team on their eligibility, and whether the student is allowed to start the Graduation Project

STUDENT DATA & MASTER PROGRAMME

Complete all fields and indicate which master(s) you are in

Family name: Saravanan

Initials:

Given name: Karthi

Student number: 5716187

IDE master(s): IPD ✔ DfI ☐ SPD ☐

2nd non-IDE master:

Individual programme *(date of approval)*:

Medisign ☐

HPM ☐

SUPERVISORY TEAM

Fill in he required information of supervisory team members. If applicable, company mentor is added as 2nd mentor

Chair: Evangelos Niforatos — dept./section: Sustainable Design Engineering

mentor: Tianhao He — dept./section: Sustainable Design Engineering

2nd mentor:

client:

city: — country:

optional comments: This graduation project is part of a broader PhD thesis research trajectory (mentor) on video-based design research. It requires computational skillset (mentor) and AI competencies (chair) that are not available outside the KInD section and SDE.

! Ensure a heterogeneous team. In case you wish to include team members from the same section, explain why.

! Chair should request the IDE Board of Examiners for approval when a non-IDE mentor is proposed. Include CV and motivation letter.

! 2nd mentor only applies when a client is involved.

APPROVAL OF CHAIR on PROJECT PROPOSAL / PROJECT BRIEF -> to be filled in **by the Chair** of the supervisory team

Sign for approval (Chair)

Name Evangelos Niforatos — Date 27.02.2024 — Signature

CHECK ON STUDY PROGRESS

To be filled in **by SSC E&SA** (Shared Service Centre, Education & Student Affairs), after approval of the project brief by the chair. The study progress will be checked for a 2nd time just before the green light meeting.

Master electives no. of EC accumulated in total ______ EC

Of which, taking conditional requirements into account, can be part of the exam programme ______ EC

☐	**YES**	all 1st year master courses passed
☐	**NO**	missing 1st year courses

Comments:

Sign for approval (SSC E&SA)

Name ______ Date ______ Signature ______

APPROVAL OF BOARD OF EXAMINERS IDE on SUPERVISORY TEAM -> to be checked and filled in by IDE's Board of Examiners

Does the composition of the Supervisory Team comply with regulations?

YES	☐	Supervisory Team approved
NO	☐	Supervisory Team not approved

Comments:

Based on study progress, students is ...

☐	**ALLOWED** to start the graduation project
☐	**NOT** allowed to start the graduation project

Comments:

Sign for approval (BoEx)

Name ______ Date ______ Signature ______

Personal Project Brief – IDE Master Graduation Project

Name student Karthi Saravanan

Student number 5716187

PROJECT TITLE, INTRODUCTION, PROBLEM DEFINITION and ASSIGNMENT
Complete all fields, keep information clear, specific and concise

Project title LLM-Powered Visual Content Extraction tool

Please state the title of your graduation project (above). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.

Introduction

Describe the context of your project here; What is the domain in which your project takes place? Who are the main stakeholders and what interests are at stake? Describe the opportunities (and limitations) in this domain to better serve the stakeholder interests. (max 250 words)

Designers often face the need to acquire knowledge in diverse topics for their projects, be it educational, cultural, research or finding inspiration for designing. Currently, designers invest significant time and effort in watching lengthy content videos and reading extensive papers to gain proficiency in diverse areas. Secondly designers also take videos of user testing scenarios to obtain insights on user behaviour.

Stakeholders, primarily designers, can benefit from swift comprehension of the video content critical to their projects. Visual representations have proven to be more effective in conveying information rapidly and are known to enhance understanding of the context and emotions. They also help to grasp a topic quickly and helps to store it in your memory easily.

Key opportunities lie in transforming intricate educational content into easily comprehensible sketches, aiding educators and learners. Additionally, the creation of compelling visuals for concept videos and product presentations, enhances the effectiveness of communication. Designers can quickly assimilate new concepts and articulate their ideas through sketching, and promoting efficient project workflows.

➔ *space available for images / figures on next page*

click to add picture

image / figure 1

image / figure 2

Problem Definition

What problem do you want to solve in the context described in the introduction, and within the available time frame of 100 working days? (= Master Graduation Project of 30 EC). What opportunities do you see to create added value for the described stakeholders? Substantiate your choice.
(max 200 words)

My focus is on addressing the challenge faced by designers who encounter the time-consuming and complex process of learning and analysing from videos, particularly through the utilisation of visual representations.
I aim to facilitate and simplify this learning process by developing a tool that leverages visuals to facilitate easier and quicker comprehension of larger subjects. This tool aims to bridge this gap by extracting content from videos and visually representing it in the form of visual sketches or pictorial mindmaps.

Existing tools in the market predominantly prioritise visual appeal over content. While these tools excel in generating visually stunning images, they fall short in providing meaningful representations for complex concepts. The tool aims to generate content-rich visual representations with the main goal to accurately represent the contents of the video in a single image.

Overall, this tool responds to the growing need for efficient knowledge transfer within the design community. The emphasis on content-rich visuals distinguishes it as a valuable asset for designers seeking rapid understanding and effective communication in their projects.

Assignment

This is the most important part of the project brief because it will give a clear direction of what you are heading for. Formulate an assignment to yourself regarding what you expect to deliver as result at the end of your project. (1 sentence) As you graduate as an industrial design engineer, your assignment will start with a verb (Design/Investigate/Validate/Create), and you may use the green text format:

Develop a prototype to improve the video based learning experience for designers by generating content rich pictorial sketches from videos.

Then explain your project approach to carrying out your graduation project and what research and design methods you plan to use to generate your design solution (max 150 words)

1. Conducting a comparative analysis of existing image generation tools involves evaluating strengths and weaknesses in conveying topics, considering aspects like visual appeal and content conveyance.

2. To validate the proposed application's benefits for designers, user studies with interviews and questionnaires will gather insights into current learning challenges. Prototypes will be shared for feedback on usability, effectiveness, and relevance.

3. The project aims to select the most effective representation style through experimentation with various visual styles, including infographics, concept maps, storyboards, cartoons, or interactive diagrams.

4. A functional prototype will be deployed and continuously refined based on testing results to align with designers' identified needs and preferences.

Project planning and key moments

*To make visible how you plan to spend your time, you must make a planning for the full project. You are advised to use a Gantt chart format to show the different phases of your project, deliverables you have in mind, meetings and in-between deadlines. Keep in mind that all activities should fit within the given run time of 100 working days. Your planning should include a **kick-off meeting**, **mid-term evaluation meeting**, **green light meeting** and **graduation ceremony**. Please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any (for instance because of holidays or parallel course activities).*

Make sure to attach the full plan to this project brief.
The four key moment dates must be filled in below

Kick off meeting 23.02.2024

Mid-term evaluation 25.04.2024

Green light meeting 27.06.2024

Graduation ceremony 22.07.2024

In exceptional cases (part of) the Graduation Project may need to be scheduled part-time. Indicate here if such applies to your project

Part of project scheduled part-time	
For how many project weeks	
Number of project days per week	

Comments:

Motivation and personal ambitions

Explain why you wish to start this project, what competencies you want to prove or develop (e.g. competencies acquired in your MSc programme, electives, extra-curricular activities or other).

Optionally, describe whether you have some personal learning ambitions which you explicitly want to address in this project, on top of the learning objectives of the Graduation Project itself. You might think of e.g. acquiring in depth knowledge on a specific subject, broadening your competencies or experimenting with a specific tool or methodology. Personal learning ambitions are limited to a maximum number of five.
(200 words max)

I have been amazed and sometimes even intimidated by the incredible logical reasoning skills that LLMs display. I am eager to tap into the power of computing and data processing to solve problems and create solutions that were unimaginable a decade ago. I have a strong desire to learn everything that goes behind creating such products, from the initial prototyping and testing stages to ensuring their safety, reliability and social impact.

I also want to infuse a human centered approach into my design, and create something that can establish better collaborations between humans and computers. As designers, we are constantly evolving and growing, both in our skills and interests. I aspire to create a product that can cater to our dynamic needs and passion to learn newer topics. Moreover, I think the faculty of IDE is the perfect place to experiment with hybrid intelligence, using LLMs, and to design a product that can work in harmony with humans and not undermine them.

WEEKLY GANTT CHART TEMPLATE

PROJECT TITLE

THESIS PLANNING

PROJECT MANAGER

Karthi Saravanan

TASK ID	TASK TITLE	Duration
1	Knowledge Gaining	14
1.1	Kick-Off Meeting	
1.2	Machine Learning Fundamentals	
1.3	Python, Deep Learning, Math Functions	
1.4	Data Collection and Preprocessing	
1.5	Techniques and Models (GAN, VAE, DAll-E)	
2	Building and Testing	27
2.1	Framework - Encoding and Decoding	
2.2	Build Model	
2.3	Train with Data sets	
2.4	Testing	
2.5	Research Setup, Plan for Q2	
2.6	Midterm Evaluation Form	
2.7	Midterm Evaluation	
3	Project Launch and Execution	44
3.1	Conduct User testing	
3.2	Process results and feedback	
3.3	Choosing Visual style	
3.3.1	Prototyping different styles	
3.4	Prototyping Iteration	
3.5	Conclusion and Results	
3.6	Write report	
3.7	Green Light	
4	Report and Presentation	17
4.1	Project Wrap-up	
4.2	Finish report	
4.3	Prepare Presentation	
4.4	Presentation day