[Inner endpaper]

HEC MONTRÉAL
École affiliée à l'Université de Montréal

An Implementation of Gaze analytic Methods to Evaluate Users Performance and Interface Learnability

Par
Jia Xuan Zheng

Constantinos Coursaris
HEC Montréal
Directeur de recherche

Alexander John Karran
HEC Montréal
Co-directeur de recherche

Sciences de la gestion
(Spécialisation Expérience Utilisateur)

Mémoire présenté en vue de l'obtention
du grade de maîtrise de sciences en gestion
(M. Sc.)

April 2025

Résumé

L'essor récent des avancées technologiques appelle à la conception d'interfaces conviviales avec une capacité d'apprentissage substantielle, un aspect crucial de l'expérience de l'utilisateur. La facilité d'apprentissage peut être définie comme la mesure dans laquelle les produits et services numériques permettent aux utilisateurs de se familiariser rapidement avec eux et de faire bon usage de toutes leurs fonctionnalités et capacités. Son rôle est crucial, car elle peut avoir un impact sur la capacité de l'utilisateur à comprendre et à utiliser une plateforme numérique. Le présent article vise à identifier les heuristiques de l'oculométrie qui sont associées à une interface intuitive, offrant ainsi la possibilité de quantifier la facilité d'apprentissage d'une interface à l'aide de données en temps réel. Trente-trois participants ont regardé une vidéo d'instruction et ont ensuite tenté de reproduire la tâche démontrée sur une nouvelle interface afin d'évaluer la capacité d'apprentissage de la première utilisation de l'interface. Les mesures de suivi du regard - y compris l'entropie de transition du regard (GTE), le coefficient K, la distance de Levenshtein et la longueur des trajets du regard - ont été analysées en même temps que le taux de réussite de la tâche et le temps d'achèvement de la tâche. Les résultats suggèrent que la condition de participation active a donné lieu à des modèles de regard moins prévisibles, mais plus concentrés et plus efficaces. En outre, les personnes performantes affichent systématiquement des comportements de regard plus concentrés et moins chaotiques. Ensemble, ces résultats appellent à la conception d'interfaces qui encouragent l'exploration naturelle de l'utilisateur et suggèrent que l'intégration des mesures du regard dans les évaluations de l'utilisabilité pourrait fournir une évaluation plus nuancée et objective de l'apprenabilité en se concentrant sur les mesures de l'attention visuelle.

Mots-clés : *Entropie de transition du regard, Attention visuelle, Dispersion de l'attention, Apprenabilité, Eye-tracking, Conception d'interface*

Abstract

Recent surge in technological advances calls for the design of user-friendly interfaces with substantiated learnability, a crucial aspect of user experience. Learnability can be referred to as the extent to which digital products and services allow users to quickly become familiar with them and make good use of all their features and capabilities. Its role is crucial, as it can impact user's ability to understand and use a digital platform. The present paper aims to identify eye-tracking gaze heuristics that are associated with an intuitive interface, offering the possibility to quantity the learnability of an interface with real-time data. Thirty-three participants watched an instructional video and subsequently attempted to replicate the demonstrated task on a novel interface in an attempt to evaluate the first-use learnability of the interface. Eye-tracking metrics — including gaze transition entropy (GTE), coefficient *K*, Levenshtein distance, and gaze path lengths — were analyzed alongside task success rate and task completion time. Results suggest that the active participation condition yielded less predictable, yet more focused and effortful gaze patterns. Additionally, high performers consistently exhibited more focused and less chaotic gaze behaviors. Together, these findings call for the design of interfaces that encourage natural user exploration and suggest that integrating gaze metrics into usability assessments could provide a more nuanced and objective evaluation of learnability by focusing on visual attentional measures.

Keywords: *Gaze Transition Entrop, Visual Attention, Attention Dispersion, Learnability, Eye-tracking, Interface Design*

Table of Contents

List of tables

List of figures

List of abbreviations and acronyms

AOI – Area of Interest

UX – User Experience

HCI – Human-computer Interaction

GTE – Gaze Transition Entropy

GTM – Gaze Transition Matrix

RQ – Research Question

Foreword

The request for the submission of the thesis was approved by the administrative management of the MSc. User Experience program. Authorization of an article format thesis was granted by the Academic Affairs Office.

This study was financed by the National Sciences and Engineering Research Council of Canada (NSERC) and PROMPT. All co-authors of this thesis have provided their written consent to be included in thesis. The authors declare that they have no known competing financial interests of personal relationships that could have appeared to influence the work reported in this paper.

The ethics approval for this project was provided on 2024-05-09 by the ethics committee at HEC Montreal under the project number 2024-5919 (See appendix A).

I declare that I have made an agreement with the supervising person or committee for my project regarding how I use generative artificial intelligence to produce the deliverables for my thesis or supervised project (See appendix C).

Acknowledgements

This thesis would have not been possible without the support of my co-directors from the Tech3Lab Pierre-Majorique Léger, Sylvain Sénécal, and Constantinos Coursaris. From the beginning, they provided unwavering support and the most supportive environment a student could ask for. I would also like to express my deepest appreciation to my thesis co-supervisors, Constantinos Coursaris and Alexander-John Karran, for their invaluable patience and feedback throughout this entire thesis writing process. They challenged me to think deeper, question new knowledge, which ultimately resulted in an incredible learning experience.

Many thanks to the Tech3lab operational team, research assistants, and Shang Lin Chen, the Tech3lab statistician who generously provided time, knowledge and expertise.

I would also thank the Social Sciences and Humanities Research Council (SSHRC), NSERC, PROMPT, and the industrial partners who were involved in the funding of this research project. Their generous contribution allowed for novel research insights, which will benefit many others.

Lastly, I am so grateful for my family, friends, and my partner who kept me happy and motivated throughout this journey. They encouraged me, believed in me, and pushed me to be the best version of myself. I love you all so much.

Chapter 1: Introduction

1.1 Context of thesis

Learnability research has emerged as a subset of user experience studies. This field investigates how users acquire proficiency with increasingly complex new interfaces, applications, and technological systems. In the past few years, the importance of learnability has gained significance due to the rapid digitalization of services and products has made digital interfaces and integral part of daily life. New technologies such as artificial intelligence, augmented reality, and complex software systems all require users to continuously adapt and learn, making user adoption and interface learnability crucial factors in product success or failure.

Among many sectors, business has seen the digital transformation by the adoption and implementation of new and emerging digital technology. Successful interactions with these interfaces directly impact user productivity, satisfaction, and overall streamlines business operations. With current interfaces becoming more complex with their expanding feature sets, users are expected to learn and adopt new systems more frequently and require users to learn independently. Research has found that every dollar invested in ease of use returns $10 to $100, highlighting the economic impact of learnability (Pressman, 2009). In the context of enterprise software, a report by Forrester Research revealed that improved user experience, including learnability, can increase conversion rates by up to 400% (Forrester, 2019). Additionally, good learnability leads to adequate productivity during the learning phase, thus ensuring better satisfaction among new users (Rafique et al., 2012). Increases in labour productivity are integral to long run improvements in living standards. Among others, improvements in labour productivity comes from growth in multifactor productivity, which are improvements in business efficiency that are attributed to innovation and technological change (Gellatly & Gu, 2024).

In recent years, learnability research incorporated diverse and mixed methodologies. From traditional usability metrics to more advanced eye-tracking technology, these tools were used to gather deeper insights into how users develop mental models and acquire new skills (Tullis & Albert, 2008). However, despite recent advances, there are still challenges in learnability research, such as the lack of standardized methods for evaluating learnability across different types of interfaces. Developing standardized methods for evaluating learnability is crucial for advancing both the theoretical and practical application of user experience design (Unsöld, 2018). While subjective methods like surveys and think-aloud protocols provide valuable insights, they often fail to capture subtle cognitive processes and unconscious user behaviours that are key for understanding learnability. Therefore, as interfaces become more complex and incorporate emerging technologies like AI, the need for sophisticated objective measurement tools becomes increasingly critical for understanding how users adopt a novel interface.

One emerging tool in HCI research is eye-tracking, a method that offers insight into users' attentional and cognitive processes (Carter & Luke, 2020; Krejtz et al., 2015). By recording where users look during a task, thus generating the patterns of their visual exploration, eye-tracking technology provides quantifiable data that helps identify usability issues that traditional methods might miss. For example, Apple, the giant of technology has recently made many advances with its forward-thinking gaze-analytic assistive technology, allowing physically impaired individuals to enjoy their products. Their human-centered strategy reduces user frustration and support needs and provides a competitive advantage in the digital marketplace. As technology continues to evolve at an unprecedented pace, understanding and improving learnability becomes not just a design consideration but a crucial factor in ensuring digital inclusion and effective technology adoption across diverse user populations.

As such, eye-tracking technology offers valuable benefits when used in HCI studies. Based on the eye-mind hypothesis (Just & Carpenter, 1976) —which suggests that there is a relationship between visual scanning behavior and one's cognitive activity— eye-tracking is a non-invasive and objective method that uncovers visual behaviours of individuals, allowing inferences related to psychological processes, such as attention or cognitive load (Molina et al., 2024). As evidenced by literature, eye-tracking captures multiple physiological and behavioral indicators, including fixation patterns, saccadic movements, gaze transitions, and pupil dilation. Among these metrics, pupil dilation has emerged as a well-established proxy for measuring cognitive load, with research consistently demonstrating that increased pupil diameter correlates with higher mental effort and processing demands (Just & Carpenter, 1976). Similarly, gaze transition patterns reveal attentional allocation strategies, while fixation duration and spatial distribution provide insights into information processing sequences. Thus, this comprehensive suite of gaze metrics can provide detailed insights into how users visually interact with interfaces and content, which can help practitioners and researchers to create more tailored experiences (Molina et al., 2024).

Although eye-tracking technology offers valuable insights into user gaze behaviors, it also presents some limitations when evaluating interface learnability. For instance, while eye-tracking can capture users attentional processes, it does not capture the participant's thought process or emotional state, calling for the need of supplementary methods, such as psychometric questionnaires to interpret the cognitive and emotional responses that gaze data alone cannot provide (Asan & Yang, 2015). Additionally, the validity of eye-tracking data in learnability studies faces both technical and interpretative challenges. Technical limitations encompass data loss and calibration issues, while the interpretation of extensive raw data requires robust theoretical grounding to avoid misattribution of cognitive processes (Poole & Ball, 2006). Furthermore, individuals have idiosyncratic temporal and spatial patterns of eye movements, which can introduce a layer of complexity when interpreting eye-tracking data (Andrews & Coppola, 1999).

1.2 Research Question

Thus, given the benefits and limitations of eye-tracking identified, our research leverages eye-tracking to identify common gaze behaviors associated with a highly learnable interface. By focusing on multiple eye-tracking metrics, including gaze transition patterns, gaze entropy measures, and pupil dilation as a proxy for cognitive load, we aim to establish objective indicators of interface learnability. This study shifts from traditional subjective methods to data-driven metrics that quantify user learning and navigation. Our multi-metric approach allows us to capture different dimensions of interface learnability: gaze patterns reveal attentional strategies and navigation behaviors, entropy measures quantify the predictability and efficiency of visual exploration, while pupil dilation provides insights into the cognitive effort required during task performance. Additionally, psychometric questionnaires will be employed to infer users' cognitive processes, providing a more nuanced interpretation of gaze behavior and enhancing the depth of our findings. As such, this research aims to explore the following research question:

> **RQ** – To what extent can gaze transition heuristics assess the learnability of an interface?

1.3 Contributions

From a methodological standpoint, this thesis contributes to the development of learnability assessment methods in HCI research by introducing eye-tracking technology as a prospective tool. Eye-tracking offers significant advantages for assessing interface learnability by providing non-invasive, cost-effective means to collect objective data (Asan & Yang, 2015). This technology captures real-time measurements of users' visual attention and gaze behavior, revealing their cognitive processes and information-seeking strategies as they learn new interfaces (Carter & Luke, 2020). Such direct insights into user behavior during system familiarization address the limitations of traditional evaluation methods. Furthermore, this study also contributes to the larger body of literature on using novel gaze analytic methods such as gaze transition entropy values and k-coefficient values to evaluate and quantify multimedia visual scenes. The implementation of these novel gaze analytic methods will provide a more comprehensive assessment framework of interface learnability.

From a theoretical standpoint, this research extends existing frameworks in cognitive science and human-computer interaction. It builds upon foundational work in scanpath theory (Noton & Stark, 1971) by providing empirical evidence of how visual attention patterns evolve during interface learning. By examining these patterns within multimedia learning environments, this study advances our understanding of the relationship between visual behavior, cognitive processing, and task performance (Krejtz et al., 2016). This integration of theoretical perspectives offers new insights into how users develop systematic viewing strategies while learning novel interfaces.

1.4 Thesis Structure

This thesis is structured into one scientific article addressed to the HCI community, and a managerial article addressed to the wider User Experience (UX) research and practitioner community. Chapter 1 will cover the first article and address the methodological aspect of this research and answer the research questions related to this problematic. Chapter 2 will address the managerial article, where one can find recommendations for designing systems that prioritize usability for accessibility. The following paragraphs will provide a summary of each article.

The second chapter of this thesis provides literature background on the current methods and tools that are used to assess learnability, and the metrics that will be used to quantify learnability. A controlled laboratory experiment involving 33 participants is conducted to establish the gaze heuristics that are relevant in effective interface design. This chapter is being prepared for submission to the journal *International Journal of Human-Computer Studies*.

The third chapter of this thesis provides a managerial article addressed to practitioners and professionals across various industries who are interested of using gaze methods to analyze their systems. Additionally, this article provides guidance on how to design better interfaces who aim to ease user adoption. This chapter is being prepared for submission to ACM SIGCHI.

1.5 Student Contributions and Responsibilities

The following table conveys my personal intellectual contribution in each aspect of the thesis. The following student was conducting in the Tech3Lab. According to the standards of the lab, an overall level of 50% in contribution is expected by the student. For dimensions where my personal contribution exceeds 50%, it suggests leadership and ownership of the corresponding phase (see table 1).

Stage in the process	Contribution
Research Question	Identified gaps in the current literature and defined the research problem and its implications [55%] - Tech3Lab co-directors helped refine the research problems - Defined research questions and identified the constructs to be tested.
Literature review	Conduct relevant research, reading scientific articles related to the topic [90%] - Tech3Lab co-directors provided feedback and comments
Experimental design	Designing and development of the experimental protocol [50%] - Tech3Lab members helped design the experimental protocol Determining the operational stimuli [80%]

	- Thesis supervisors and Tech3Lab research team approved the operational stimuli Applying to the CER [50%] - Tech3Lab members helped prepare the documentation related to the submission of the application to the CER
Data Collection	Recruitment of participants [30%] - Tech3lab recruited all participants through Panelfox - Provided the criteria for participation for the study Pre-testing and data collection operations management [50%] - Recruited and pre-tested with 10 participants with the assistance of Tech3Lab research assistants - Designed and tested experiment conditions Collecting data [50%] - Oversaw the entire data collection process and operations - Tech3Lab research team moderated the study and distributed the compensation to participants
Statistical Analysis	Performing statistical analysis [55%] - Extraction and treatment of the data to synchronize all instruments by Tech3Lab Statistician Shang Lin - Programming of statistical analyses on SAS revised and approved by the Tech3Lab Statistician Shang Lin - Interpretation and synthesis of the results by the student
Thesis writing	Redaction of thesis and articles [80%] - Thesis co-supervisors provided comments and corrections to my drafts

Table 1.Student contributions and related responsibilities in this thesis.

References

Andrews, T. J., & Coppola, D. M. (1999). Idiosyncratic characteristics of saccadic eye movements when viewing different visual environments. *Vision Research*, *39*(17), 2947-2953. https://doi.org/https://doi.org/10.1016/S0042-6989(99)00019-X

Asan, O., & Yang, Y. (2015). Using Eye Trackers for Usability Evaluation of Health Information Technology: A Systematic Literature Review. *JMIR Hum Factors*, *2*(1), e5. https://doi.org/10.2196/humanfactors.4062

Baecker, R., Booth, K., Jovicic, S., McGrenere, J., & Moore, G. (2000). *Reducing the gap between what users know and what they need to know* Proceedings on the 2000 conference on Universal Usability, Arlington, Virginia, USA. https://doi.org/10.1145/355460.355467

Bergstrom, J. R., & Schall, A. (2014). *Eye Tracking in User Experience Design*. Morgan Kaufmann Publishers Inc.

Bevan, N., & Macleod, M. (1994). Usability measurement in context. *Behaviour & Information Technology*, *13*(1-2), 132-145. https://doi.org/10.1080/01449299408914592

Beymer, D., & Russell, D. M. (2005). *WebGazeAnalyzer: a system for capturing and analyzing web reading behavior using eye gaze* CHI '05 Extended Abstracts on Human Factors in Computing Systems, Portland, OR, USA. https://doi.org/10.1145/1056808.1057055

Brooke, J. (1995). SUS: A quick and dirty usability scale. *Usability Eval. Ind.*, *189*.

Burr, D. (2011). Visual Perception: More Than Meets the Eye. *Current Biology*, *21*(4), R159-R161. https://doi.org/https://doi.org/10.1016/j.cub.2011.01.007

Butler, K. A. (1985). *Connecting theory and practice: a case study of achieving usability goals* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, San Francisco, California, USA. https://doi.org/10.1145/317456.317472

Carbonell, I., de la Fuente, J., & Afriyie, P. (2019). *Using Mobile Eye Tracking and Coefficient K for Analysing Usability Trials*.

Carroll, J. M., Mack, R. L., Lewis, C. H., Grischkowsky, N. L., & Robertson, S. R. (1985). Exploring Exploring a Word Processor. *Human–Computer Interaction*, *1*(3), 283-307. https://doi.org/10.1207/s15327051hci0103_3

Carter, B. T., & Luke, S. G. (2020). Best practices in eye tracking research. *International Journal of Psychophysiology*, *155*, 49-62. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2020.05.010

Davies, A., Harper, S., Vigo, M., & Jay, C. (2018). Using simultaneous scanpath visualization to investigate the relationship between accuracy and eye movement during medical image interpretation. *J Eye Mov Res*, *10*(5). https://doi.org/10.16910/jemr.10.5.11

Davis, S., & Wiedenbeck, S. (1998). The effect of interaction style and training method on end user learning of software packages. *Interacting with Computers*, *11*(2), 147-172. https://doi.org/10.1016/S0953-5438(98)00026-5

De Bruyne, J., Leersnijder, L., Talsma, D., Demanet, J., Saldien, J., & Bombeke, K. (2024). *Random Gazes, Telling Eyes: Exploring Gaze Transition Entropy as a Performance Indicator in Evaluating Instructional Designs*. https://doi.org/10.54941/ahfe1004747

Dix, A., Finlay, J., Abowd, G., & Beale, R. (2004). Human-Computer Interaction. In.

Duchowski, A. (2007). *Eye Tracking Methodology: Theory and Practice*. https://doi.org/10.1007/978-1-84628-609-4

Eckstein, M. K., Guerra-Carrillo, B., Miller Singley, A. T., & Bunge, S. A. (2017). Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? *Developmental Cognitive Neuroscience*, *25*, 69-91. https://doi.org/https://doi.org/10.1016/j.dcn.2016.11.001

Egeth, H. E., & Yantis, S. (1997). Visual attention: control, representation, and time course. *Annu Rev Psychol*, *48*, 269-297. https://doi.org/10.1146/annurev.psych.48.1.269

Elliott, G. J., Jones, E., & Barker, P. (2002). A grounded theory approach to modelling learnability of hypermedia authoring tools. *Interacting with Computers*, *14*(5), 547-574. https://doi.org/https://doi.org/10.1016/S0953-5438(02)00021-8

Ericsson, K. A., & Simon, H. A. (1984). *Protocol analysis: Verbal reports as data*. The MIT Press.

Fahimi, R., & Bruce, N. D. B. (2021). On metrics for measuring scanpath similarity. *Behavior Research Methods*, *53*(2), 609-628. https://doi.org/10.3758/s13428-020-01441-0

Frey, J., Mühl, C., Lotte, F., & Hachet, M. (2014). *Review of the Use of Electroencephalography as an Evaluation Method for Human-Computer Interaction*.

Gilbert, C. D., & Li, W. (2013). Top-down influences on visual processing. *Nature Reviews Neuroscience*, *14*(5), 350-363. https://doi.org/10.1038/nrn3476

Goldberg, J., & Kotval, X. (1999). Computer interface evaluation using eye movements: Methods and constructs. *International Journal of Industrial Ergonomics*, *24*, 631-645. https://doi.org/10.1016/S0169-8141(98)00068-7

Grondin, S. (2016). *Psychology of Perception* (Vol. 1). Springer Cham.

Grossman, T., Fitzmaurice, G., & Attar, R. (2009). *A survey of software learnability: metrics, methodologies and guidelines* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, MA, USA. https://doi.org/10.1145/1518701.1518803

Guo, Y., Pannasch, S., & Helmert, J. R. (2022). *Eye Movements in Extended Tasks: Analyses of Ambient/Focal Attention with Coefficient K* 2022 Symposium on Eye Tracking Research and Applications, Seattle, WA, USA. https://doi.org/10.1145/3517031.3529630

Hayes, T. R., Petrov, A. A., & Sederberg, P. B. (2011). A novel method for analyzing sequential eye movements reveals strategic influence on Raven's Advanced Progressive Matrices. *Journal of Vision*, *11*(10), 10-10. https://doi.org/10.1167/11.10.10

Hessels, R. S., Kemner, C., van den Boomen, C., & Hooge, I. T. C. (2016). The area-of-interest problem in eyetracking research: A noise-robust solution for face and sparse stimuli. *Behavior Research Methods*, *48*(4), 1694-1712. https://doi.org/10.3758/s13428-015-0676-y

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). Eye Tracking: A Comprehensive Guide To Methods And Measures.

Howes, A., & Young, R. M. (1993). Predicting the learnability of task-action mappings. In *The Soar papers (vol. II): research on integrated intelligence* (pp. 1204–1209). MIT Press.

[ISO], I. O. f. S. (2011). ISO/IEC 25010:2011. In.

[ISO], I. O. f. S. (2023). ISO/IEC 25010:2023. In.

Just, M. A., & Carpenter, P. A. (1976). Eye fixations and cognitive processes. *Cognitive Psychology*, *8*(4), 441-480. https://doi.org/https://doi.org/10.1016/0010-0285(76)90015-3

Kellermann, T., Regenbogen, C., De Vos, M., Mößnang, C., Finkelmeyer, A., & Habel, U. (2012). Effective connectivity of the human cerebellum during visual attention. *J Neurosci*, *32*(33), 11453-11460. https://doi.org/10.1523/jneurosci.0678-12.2012

Klatt, S., & Memmert, D. (2021). Studying Spatial Visual Attention: The Attention-Window Task as a Measurement Tool for the Shape and Maximum Spread of the Attention Window [Original Research]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.614077

Krejtz, I., Szarkowska, A., Krejtz, K., Walczak, A., & Duchowski, A. (2012). Audio description as an aural guide of children's visual attention: Evidence from an eye-tracking study. *Eye Tracking Research and Applications Symposium (ETRA)*. https://doi.org/10.1145/2168556.2168572

Krejtz, K., Çöltekin, A., Duchowski, A., & Niedzielska, A. (2017). Using Coefficient to Distinguish Ambient/Focal Visual Attention During Cartographic Tasks. *J Eye Mov Res*, *10*(2). https://doi.org/10.16910/jemr.10.2.3

Krejtz, K., Duchowski, A., Szmidt, T., Krejtz, I., Perilli, F. G., Pires, A., Vilaro, A., & Villalobos, N. (2015). Gaze Transition Entropy. *ACM Trans. Appl. Percept.*, *13*(1), Article 4. https://doi.org/10.1145/2834121

Krejtz, K., Duchowski, T. A., Krejtz, I., Kopacz, A., & Chrząstowski-Wachtel, P. (2016). Gaze transitions when learning with multimedia. *Journal of Eye Movement Research*, *9*(1). https://doi.org/10.16910/jemr.9.1.5

Krejtz, K. a. D. A. a. K. I. a. S. A. a. K. A. (2016). Discerning Ambient/Focal Attention with Coefficient K. *ACM Trans. Appl. Percept.*, *13*(3). https://doi.org/10.1145/2896452

Lanini-Maggi, S., Ruginski, I. T., Shipley, T. F., Hurter, C., Duchowski, A. T., Briesemeister, B. B., Lee, J., & Fabrikant, S. I. (2021). Assessing how visual search entropy and engagement predict performance in a multiple-objects tracking air traffic control task. *Computers in Human Behavior Reports*, *4*, 100127. https://doi.org/https://doi.org/10.1016/j.chbr.2021.100127

Lewis, J. R., & Sauro, J. (2009, 2009//). The Factor Structure of the System Usability Scale. Human Centered Design, Berlin, Heidelberg.

Lin, H. X., Choong, Y.-Y., & Salvendy, G. (1997). A proposed index of usability: A method for comparing the relative usability of different software systems. *Behaviour & Information Technology*, *16*(4-5), 267-277. https://doi.org/10.1080/014492997119833

Linja-aho, M. (2005). Evaluating and Improving the Learnability of a Building Modeling System. In. Helsinki: University of Technology

Liversedge, S., Gildchrist, I., & Everling, S. (2011). *The Oxford handbook of eye movements* [doi:10.1093/oxfordhb/9780199539789.001.0001]. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199539789.001.0001

Mackamul, E., Casiez, G., & Malacria, S. (2024). Clarifying and differentiating discoverability. *Human–Computer Interaction*, *0*(0), 1-26. https://doi.org/10.1080/07370024.2024.2364606

Marrella, A., & Catarci, T. (2018). *Measuring the Learnability of Interactive Systems Using a Petri Net Based Approach* Proceedings of the 2018 Designing Interactive Systems Conference, Hong Kong, China. https://doi.org/10.1145/3196709.3196744

Michelsen, C. D., Dominick, W. D., & Urban, J. E. (1980). *A methodology for the objective evaluation of the user/system interfaces of the MADAM system using software engineering principles* Proceedings of the 18th annual Southeast regional conference, Tallahassee, Florida. https://doi.org/10.1145/503838.503847

Molina, A. I., Arroyo, Y., Lacave, C., Redondo, M. A., Bravo, C., & Ortega, M. (2024). Eye tracking-based evaluation of accessible and usable interactive systems: tool set of guidelines and methodological issues. *Universal Access in the Information Society*. https://doi.org/10.1007/s10209-023-01083-x

Monsell, S., & Driver, J. (2000). *Control of Cognitive Processes: Attention and Performance XVIII*. https://doi.org/10.7551/mitpress/1481.001.0001

Nahlik, P., & Daubenmire, P. L. (2022). Adapting gaze-transition entropy analysis to compare participants' problem solving approaches for chemistry word problems [10.1039/D2RP00066K]. *Chemistry Education Research and Practice*, *23*(3), 714-724. https://doi.org/10.1039/D2RP00066K

Najemnik, J., & Geisler, W. S. (2005). Optimal eye movement strategies in visual search. *Nature*, *434*(7031), 387-391.

Nguyen, C. T. O., Acosta, M. L., Di Angelantonio, S., & Salt, T. E. (2021). Editorial: Seeing Beyond the Eye: The Brain Connection [Editorial]. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.719717

Nielsen, J. (1993). Chapter 2 - What Is Usability? In J. Nielsen (Ed.), *Usability Engineering* (pp. 23-48). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-08-052029-2.50005-X

Nielsen, J. (1994). *Usability Engineering*. Morgan Kaufmann Publishers Inc.

Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

Noton, D., & Stark, L. (1971). Eye Movements and Visual Perception. *Scientific American*, *224*(6), 34-43. http://www.jstor.org/stable/24922750

Paymans, T. F., Lindenberg, J., & Neerincx, M. (2004). *Usability trade-offs for adaptive user interfaces: ease of use and learnability* Proceedings of the 9th international conference on Intelligent user interfaces, Funchal, Madeira, Portugal. https://doi.org/10.1145/964442.964512

Poole, A., & Ball, L. (2006). Eye tracking in human-computer interaction and usability research: Current status and future prospects. In (pp. 211-219).

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annu Rev Neurosci*, *13*, 25-42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Pressman, R. (2009). *Software Engineering: A Practitioner's Approach* (7 ed.). McGraw-Hill Inc.

Privitera, C. M. a. S. L. W. (2000). Algorithms for defining visual regions-of-interest: comparison with eye fixations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(9), 970-982. https://doi.org/10.1109/34.877520

Rafique, I., Weng, J., Abbasi, M., & Lew, P. (2012). *Software Learnability Evaluation An Overview of Definitions and Evaluation Methodologies for GIS Applications*.

Rai, Y., & Callet, P. L. (2018). Chapter 3 - Visual attention, visual salience, and perceived interest in multimedia applications. In R. Chellappa & S. Theodoridis (Eds.), *Academic Press Library in Signal Processing, Volume 6* (pp. 113-161). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-811889-4.00003-8

Rai, Y., & Le Callet, P. (2018). Visual attention, visual salience, and perceived interest in multimedia applications. In *Academic Press Library in Signal Processing, Volume 6* (pp. 113-161). Elsevier. https://hal.science/hal-01970944

Rieman, J. (1996). A field study of exploratory learning strategies. *ACM Trans. Comput.-Hum. Interact.*, *3*(3), 189–218. https://doi.org/10.1145/234526.234527

Santos, P. J., & Badre, A. N. (1995). Discount Learnability Evaluation.

Schall, A., & Romano Bergstrom, J. (2014). 1 - Introduction to Eye Tracking. In J. Romano Bergstrom & A. J. Schall (Eds.), *Eye Tracking in User Experience Design* (pp. 3-26). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-408138-3.00001-7

Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction*, *13*, 141-156. https://doi.org/10.1016/S0959-4752(02)00017-8

Shiferaw, B., Downey, L., & Crewther, D. (2019). A review of gaze entropy as a measure of visual scanning efficiency. *Neuroscience & Biobehavioral Reviews*, *96*, 353-366. https://doi.org/https://doi.org/10.1016/j.neubiorev.2018.12.007

Shneiderman, B., Plaisant, C., Cohen, M., & Jacobs, S. (2009). Designing the user interface: strategies for effective human-computerinteraction. *Information Design Journal*, *17*, 157-158. https://doi.org/10.1075/idj.17.2.14mar

Shulman, G. L., Wilson, J., & Sheehy, J. B. (1985). Spatial determinants of the distribution of attention. *Perception & Psychophysics*, *37*, 59-65.

Stark, L. W., & Choi, Y. S. (1996). Experimental metaphysics: The scanpath as an epistemological mechanism. In W. H. Zangemeister, H. S. Stiehl, & C. Freksa (Eds.), *Advances in Psychology* (Vol. 116, pp. 3-69). North-Holland. https://doi.org/https://doi.org/10.1016/S0166-4115(96)80069-0

Stevens, C., & Bavelier, D. (2012). The role of selective attention on academic foundations: a cognitive neuroscience perspective. *Dev Cogn Neurosci*, *2 Suppl 1*(Suppl 1), S30-48. https://doi.org/10.1016/j.dcn.2011.11.001

Stickel, C., Fink, J., & Holzinger, A. (2007, 2007//). Enhancing Universal Access – EEG Based Learnability Assessment. Universal Access in Human-Computer Interaction. Applications and Services, Berlin, Heidelberg.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960-967. https://doi.org/https://doi.org/10.1016/j.promfg.2018.03.137

Tobii, A. (2022). Tobii Pro Lab User Manual (Version 1.241). In. Danderyd, Sweden.

Treue, S. (2003). Visual attention: the where, what, how and why of saliency. *Current Opinion in Neurobiology*, *13*(4), 428-432. https://doi.org/https://doi.org/10.1016/S0959-4388(03)00105-3

Tullis, T., & Albert, W. (2008). *Measuring the User Experience: Collecting, Analyzing, and Presenting Usability Metrics: Second Edition*.

Unsöld, M. (2018). Measuring Learnability in Human-Computer Interaction.

Wals, S. F., & Wichary, S. (2023). Under Pressure: Cognitive Effort During Website-Based Task Performance is Associated with Pupil Size, Visual Exploration, and Users'

Intention to Recommend. *International Journal of Human–Computer Interaction*, *39*(18), 3504-3515. https://doi.org/10.1080/10447318.2022.2098576

Wolf, C., & Lappe, M. (2021). Vision as oculomotor reward: cognitive contributions to the dynamic control of saccadic eye movements. *Cogn Neurodyn*, *15*(4), 547-568. https://doi.org/10.1007/s11571-020-09661-y

Wong, A. Y., Bryck, R. L., Baker, R. S., Hutt, S., & Mills, C. (2023). *Using a Webcam Based Eye-tracker to Understand Students' Thought Patterns and Reading Behaviors in Neurodivergent Classrooms* LAK23: 13th International Learning Analytics and Knowledge Conference, Arlington, TX, USA. https://doi.org/10.1145/3576050.3576115

World Bank. (2024). Digital Progress and Trends Report 2023. In. Washington.

Yarbus, A. L. (2013). *Eye movements and vision*. Springer.

Zakiniaeiz, Y. (2016). The Mind's Machine: Foundations of Brain and Behavior, Second Edition. In *Yale J Biol Med* (Vol. 89, pp. 110). Copyright ©2016, Yale Journal of Biology and Medicine.

Chapter 2: Methodological Study

Gaze Transition Analysis: An Implementation of Gaze Analytic Methods to Evaluate Users' Performance and Interface Learnability

Jia Xuan Zheng, Alexander-John Karran, Constantinos K. Coursaris, Pierre-Majorique Léger, and Sylvain Sénécal

Abstract

The recent surge in technological advances calls for the design of user-friendly interfaces with substantiated learnability, a crucial aspect of user experience. Learnability can be referred to as the extent to which digital products and services allow users to quickly become familiar with them and make good use of all their features and capabilities. Its role is crucial, as it can impact user's ability to understand and use a digital platform. The present paper aims to identify eye-tracking gaze heuristics that are associated with an intuitive interface, offering the possibility to quantity the learnability of an interface with real-time data. Thirty-three participants watched an instructional video and subsequently attempted to replicate the demonstrated task on a novel interface in an attempt to evaluate the first-use learnability of the interface. Eye-tracking metrics — gaze transition entropy (GTE), coefficient *K*, Levenshtein distance, and gaze path lengths — were analyzed alongside task success rate and task completion time. Results suggest that the active participation condition yielded less predictable, yet more focused and effortful gaze patterns. Additionally, high performers consistently exhibited more focused and less chaotic gaze behaviors. Together, these findings call for the design of interfaces that encourage natural user exploration and suggest that integrating gaze metrics into usability assessments could provide a more nuanced and objective evaluation of learnability by focusing on visual attentional measures.

Keywords: *Gaze transition entropy, Visual Attention, Attention Dispersion, Learnability, Eye-tracking, Interface Design*

2.1 Introduction

In today's fast-paced digital world, the need for easily learnable interfaces has become more crucial than ever. Modern users navigate through an unprecedented number of digital tools and applications daily, from workplace software to social media platforms and essential services like online banking and healthcare portals. As such, the rapid technology evolution requires users to constantly adapt to new ways of interacting with novel interfaces. Since user interfaces serve as the primary point of interaction between humans and technology, learnability, a critical aspect of interface design, directly influences how quickly and efficiently users can perform a task on a platform after initial exposure (Nielsen, 1993). Enhanced learnability in user interfaces can significantly reduce user frustration, accelerate technological adoption, and boost productivity (World Bank, 2024).

The methods used so far in the measurement of interface learnability consists mostly of psychometrics and behavioural measures (Unsöld, 2018). However, recent developments in the field of Human-Computer Interaction (HCI) suggest that eye-tracking technology is a potential tool to use by capturing real-time data on user interactions with an interface through gaze heuristics (Eckstein et al., 2017). Tracking user gaze behaviours can provide detailed insight into where users allocate their attention and their cognitive processes while they navigate through an interface. Additionally, it may also be possible to infer the characteristics of gaze behaviors that are associated with a learnable interface and provide a guideline for better interface design.

Thus, this study proposes a novel method of assessing interface learnability, utilizing eye-tracking technologies to provide rich gaze behaviour data to provide insight into the cognition of users while they are interacting with a novel interface.

2.2 Research objective

The increasing complexity of digital interfaces demands a more systematic approach to evaluating learnability. Our study explores how eye-tracking metrics, particularly gaze patterns, could provide objective measures for assessing interface learnability. Through this exploratory research, we aim to investigate whether gaze entropy and related metrics can serve as reliable indicators of how easily users can learn and navigate an interface. This approach introduces a shift from traditional subjective evaluation methods toward quantifiable, data-driven measurements of interface learnability.

RQ – To what extent can gaze transition heuristics assess the learnability of an interface?

We conducted a laboratory study with 33 participants to examine their gaze patterns while interacting with a novel interface. Going beyond traditional eye-tracking measures like saccades, fixations, and scan paths, we implemented a novel matrix analysis technique to generate more comprehensive eye movement metrics.

2.3 Literature review

2.3.1 Learnability

Definitions

The core of a good user experience (UX) is usability and utility (Bergstrom & Schall, 2014). While utility refers to "whether the functionality of the system in principle can do what is needed [...], usability is the question of how well users can use that functionality" (Nielsen, 1993).

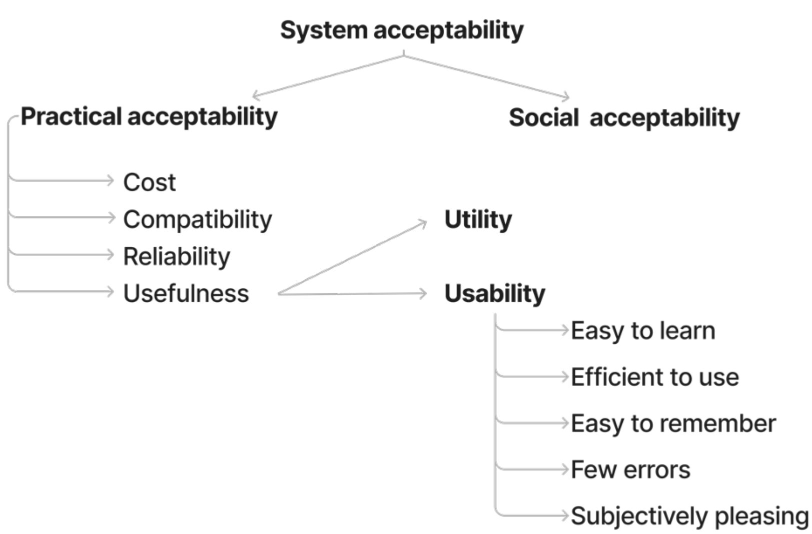


Figure 1. Model of the attributes of system acceptability, adapted from Nielsen (1993).

Usability itself is divided into multiple components and is traditionally associated with the following five usability features (see Figure 1): Learnability, efficiency, memorability, errors, and satisfaction (Nielsen, 1993). There seems to be a lack of a universally accepted definition of learnability within the Human-Computer Interaction (HCI) community. There are several broad categories of definition, ranging from definitions based on initial user learning, extended learning, to learning as a function of experience (Grossman et al., 2009).

Within the field of UX, learnability is often referred to as the extent to which digital products and services allow users to quickly become familiar with them and make good use of all their features and capabilities. While some definitions focus on initial learning "how quickly users learn to operate the software (Shneiderman et al., 2009), other definitions includes both initial and long-term learning "the ease with which new users can begin effective interaction and achieve maximal performance" (Dix et al., 2004), or "minimally useful with no formal training, and should be possible to master the software" (Rieman, 1996). One study surveyed articles published in CHI and TOCHI, in an attempt to demonstrate the differing definitions of learnability and out of the 88 papers dating from 1982 to 2008, they highlighted more than eight different categories of learnability definitions (Grossman et al., 2009).

It would also be relevant to discuss the definitions of organizations such as the International Organization for Standardization (ISO), which refer learnability as "capability of a product to have specified users learn to use specified product functions within a specified amount of time" ([ISO], 2023). This definition is slightly different from its previous version that defined learnability as "the degree to which a product or system can be used by specified users to achieve specified goals of learning to use the product of system with effectiveness, efficiency, freedom from risk and satisfaction in a specified context of use" ([ISO], 2011).

While researchers typically customize their definitions to align with the specific aspects they're investigating, all these varying interpretations share a common goal: understanding what makes a system easy for users to learn.

For the purpose of this study, we have chosen to adopt the ISO's 2011 definition of learnability for its comprehensive nature and its alignment with our objective to determine pertinent eye-tracking metrics related to learnability through measuring user performance.

2.3.2 Learnability vs. Discoverability

Similar to the concept of learnability is discoverability, a recent term that emerged in HCI research (Mackamul et al., 2024). While learnability focuses on specific aspects related to performance while also covering some period beyond initial interactions (Grossman et al., 2009), discoverability has an emphasis on the initial intuitive perception and understanding, answering the question "is it possible to even figure out what actions are possible and where and how to perform them?" (Norman, 2013). In the context of HCI research, system discoverability is focused on whether potential users notice the overall system and recognize it as something they can interact with, rather than getting familiar with how to use them.

While discoverability shapes initial user interactions, learnability is crucial for the long-term adoption of a system. Highly discoverable features might not be relevant if users fail to adopt them, directly impacting user satisfaction and sustained engagement with the system. Given its significance for user adoption and system success, this study focuses on learnability as the primary focus for evaluation.

2.3.3 The role of learnability

The role of learnability is crucial, as it can impact user's ability to understand and use a digital platform. Learnability is the most fundamental usability attribute since all users need to learn how to use a new system for the first time, which implies that most systems need to be easy to learn (Nielsen, 1993). In other words, the easier it is to learn a system, the more "intuitive" it is. In the domain of UX, the goal is to reduce the effort, time and training users need to start using an interface. A system or a software that is difficult to learn can lead to user frustration. All in all, as the world becomes increasingly digital, the demand for intuitive, user-friendly interfaces has never been greater. A deeper understanding of learnability can lead to insights on how users process information and acquire new skills in a multimedia environment and contribute to the design of digital tools that are optimized for diver user groups.

2.3.4 Existing methods of learnability evaluation

Usability evaluations can be either formative or summative (Nielsen, 1994). While formative assessments focus on the process leading to the completion of a product, summative assessment considers the final product. This distinction can also be made for learnability evaluations, where formative evaluations should expose learnability issues, while summative evaluations should assess a system's overall learnability (Grossman et al., 2009). In the category of formative learnability evaluation methodologies, there are subjective methods such as the Diary method, Think Aloud Protocol, or the Questions-Suggestion Protocol which gives insights into participants' cognitive processes but are also prone to high levels of subjectivity (Ericsson & Simon, 1984).

As for the summative learnability evaluation methodologies, there are performance-based measurements, which can be made by using the following learnability metrics that are most relevant to the system interface (see table 2). Observations are also frequently employed to conduct summative evaluations of interface learnability. For example, techniques such as Data logging, C-INCAMI framework, with a combination of several other methodologies like expert evaluations and user tests are used to investigate different aspects of usability (Rafique et al., 2012).

Task Metrics: Metrics based on task performance
T1. Percentage of users who complete a task optimally (Linja-aho, 2005).
T2. Percentage of users who complete a task without any help (Linja-aho, 2005).
T3. Ability to complete task optimally after certain time frame (Butler, 1985).
T4. Decrease in task errors made over certain time interval (Michelsen et al., 1980)
T5. Time until user completes a certain task successfully (Nielsen, 1994)
T6. Time until user completes a set of tasks within a time frame (Nielsen, 1994).
T7. Quality of work performed during a task, as scored by judges (Davis & Wiedenbeck, 1998).
Command Metrics: Metrics based on command usage
C1. Success rate of commands after being trained (Carroll et al., 1985).
C2. Increase in commands used over certain time interval (Michelsen et al., 1980).

C3. Increase in complexity of commands over time interval (Michelsen et al., 1980).
C4. Percent of commands known to user (Baecker et al., 2000).
C5. Percent of commands used by user (Baecker et al., 2000).
Mental Metrics: Metrics based on cognitive processes
M1. Decrease in average think times over certain time interval (Michelsen et al., 1980).
M2. Alpha vs. beta waves in EEG patterns during usage (Stickel et al., 2007)
M3. Change in chunk size over time (Santos & Badre, 1995).
M4. Mental Model questionnaire pretest and post test results (Paymans et al., 2004)
Subjective Metrics: Metrics based on user feedback
S1. Number of learnability related user comments (Michelsen et al., 1980).
S2. Learnability questionnaire responses (Lin et al., 1997)
S3. Twenty-six Likert statements (Elliott et al., 2002)
Documentation Metrics: Metrics based on documentation usage
D1. Decrease in help commands used over certain time interval (Michelsen et al., 1980).
D2. Time taken to review documentation until starting a task (Michelsen et al., 1980).
D3. Time to complete a task after reviewing documentation (Michelsen et al., 1980).
Usability Metrics: Metrics based on change in usability
U1. Comparing “quality of use” over time (Bevan & Macleod, 1994)
U2. Comparing “usability” for novice and expert users (Bevan & Macleod, 1994)
Rule Metrics: Metrics based on specific rules
R1. Number of rules required to describe the system (Howes & Young, 1993)

Table 2. Categories of learnability metrics, adapted from Grossman et al. (2009)

Evaluating learnability remains a significant challenge due to limitations in existing methods. Many current methods are either costly, invasive, or too reliant on subjective self-reports, which might not capture individuals' actual thoughts and cognitive processes. For example, performance-based measurements, though quantifiable, provide only surface-level insights and fail to uncover the underlying cognitive mechanisms driving these outcomes. More advanced tools like electroencephalogram answer this problem, and can provide insights into cognitive processes, but are costly, invasive and require trained experts to analyze the data (Frey et al., 2014). These limitations become more pronounced in multimedia environments, where it is required to test users' performance while they navigate complex systems and experience frequent shifts in attention (Marrella & Catarci, 2018).

As such, current methods lack to provide a non-invasive, cost-effective approach that captures objective, real-time data on individuals' cognitive processes, and attention allocation strategies while they familiarize themselves with a novel system. The next section will be dedicated to introducing eye-tracking technology as a promising solution that will address these limitations.

2.3.5 Eye-tracking in HCI research

Eye-tracking is a rich experimental method that has recently surged in popularity over the last few years (Carter & Luke, 2020). Being able to track individuals' eye movements can help HCI researchers understand visual and display-based information processing and the factors that have an influence on the usability of system interfaces (Poole & Ball, 2006). In fact, eye-tracking makes it possible to detect where users look at any point in time, how long they look at an object, and the path that their eyes follow. It can also directly capture how individuals allocate their visual attention while performing a task (Carter & Luke, 2020). By monitoring eye movements, researchers can infer real-time cognitive load, decision-making, and information processing strategies (Duchowski, 2007). This method is particularly relevant for tasks involving complex visual stimuli, allowing for a detailed analysis of how visual attention supports cognitive functions like memory, problem-solving, and learning (Eckstein et al., 2017). In UX research, eye-tracking helps researchers understand the complete user experience, which often users themselves cannot describe (Schall & Romano Bergstrom, 2014). Eye-tracking reveals patterns of focus, gaze duration, and saccadic movements, which correlate with underlying mental activities.

In modern eye-tracking technologies, gaze behaviours are tracked through an array of infrared or near-infrared light sources and cameras (Holmqvist et al., 2011). It relies on a method called corneal reflection, which detects and track the location of the eye as it moves. Corneal reflection uses a light source to illuminate the eye, which then causes a reflection of the light source on the cornea and in the pupil. Advanced image processing algorithms are then used to establish the point of gaze related to the eye and the stimuli (Bergstrom & Schall, 2014). Eye-tracking has been applied to many fields including human factors, cognitive psychology, marketing, and the broad field of human-computer interaction. In user experience research, eye tracking helps researchers understand the complete user experience, even that which users cannot describe (Bergstrom & Schall, 2014). Across all fields of research using eye-tracking as a research method, areas of interest (AOIs) are used to link eye-movement measures to parts of the stimulus used (Hessels et al., 2016).

Applications of the eye-tracker within HCI research include but does not limit to usability evaluations, understanding user behavior during interactions with systems, interface design or accessibility studies among many others (Poole & Ball, 2006). For examples, some researchers have used the eye-tracker to analyze web reading behavior, and some others to understand neurodivergent students' thought patterns (Beymer & Russell, 2005; Wong et al., 2023).

2.3.6 Eye movements and the brain

The preceding discussion highlighted numerous applications of eye-tracking, which generate a diverse array of eye-tracking metrics based on eye movements. However, questions remain regarding the interpretation of these metrics and the extent to which eye movement patterns correspond to underlying cognitive processes. An emerging area of research focuses on the use of the eye as window to changes occurring in the brain (Nguyen et al., 2021) The relationship between visual experiences and cognition emerges from complex interaction between the eyes, the brain, and the surrounding environment (Burr, 2011). According to the eye-mind hypothesis (EMH), there is a close relationship between what a person fixates on, and what their mind processes (Just

& Carpenter, 1976). Similarly, it has been suggested that eye movements provide a dynamic trace of where attention is being directed (Just & Carpenter, 1980). This relationship is particularly pertinent when evaluating individuals' gaze patterns while performing a task on a novel interface where visual attention is a key factor in understanding the cognition of users while assessing interface learnability. As such, in the context of eye-tracking research, the EMH hypothesis means that eye-movement recordings can provide a dynamic trace of where a person's attention is being directed in relation to a visual display (Poole & Ball, 2006). Eye movements thus provide a non-intrusive window into how the brain processes information during sophisticated cognitive activities.

Prior research has suggested that part of perception is also about trying to understand how preconceived concepts or mental models can influence what is going to be perceived, a phenomenon known as top-down cognitive processing (Rai & Le Callet, 2018). In this cognitive processing model, the brain's ability to guide behaviour is based on prior knowledge, expectations and goals, rather than reacting purely to external stimuli (Grondin, 2016). Top-down, also known as goal-directed attentional control is the result of the observer's deliberate state of attentional readiness (Egeth & Yantis, 1997)

The eyes and brain are closely interconnected, primarily through the optic nerve, which transmits visual information from the retina to the brain's visual cortex (Zakiniaeiz, 2016). Based on neural pathways that convey higher order information to antecedent cortical structures, top-down signals from the brain conveys rich information that helps the individual process and interpret the visual scene before them (Gilbert & Li, 2013). Beyond basic visual processing, eye movements are controlled by cognitive mechanisms in the brain that manage attention, decision-making, and memory (Wolf & Lappe, 2021). By analyzing patterns like fixations, saccades, and pupil dilation, we can infer aspects of cognitive load, emotional state, and how the brain allocates attention (Wolf & Lappe, 2021). This provides insights into mental effort, stress, and decision-making processes during complex tasks, revealing how individuals prioritize visual information and shift their attention (Najemnik & Geisler, 2005; Yarbus, 2013). Brain regions like the frontal eye fields and the prefrontal cortex modulate this voluntary, goal-driven eye-behaviour, allowing individuals to direct their gaze towards task-relevant information while filtering distractions (Treue, 2003). These areas coordinate the selection and execution of eye movements based on attentional and goal-driven demands. For instance, voluntary saccades are controlled by top-down cognitive processes, allowing the eyes to shift focus to relevant stimuli (Treue, 2003). Moreover, the basal ganglia and cerebellum help fine-tune and regulate these movements (Kellermann et al., 2012). For example, in a visual search task, top-down control enables selective attention, prioritizing important features based on goals (Posner & Petersen, 1990). These processes are crucial in controlling eye movements and support efficient task performance by optimizing visual attention and decision-making. By analyzing these eye movements, it is possible to infer how cognitive control and decision-making operate in real-time (Duchowski, 2007).

2.3.7 Attention: Stimulus-driven and goal-oriented

Another interesting cognitive process to highlight in the study of visual interactions with a novel interface is visual attention, another important component of higher-level cognition, which refers to attentional processes that allows for the selective processing of day-to-day information (Stevens & Bavelier, 2012). William James (1890) made an important distinction in how attention works. He identified two main types of attention: passive and active attention. In more recent terms, passive attention is referred to as "bottom-up" or "stimulus-driven" attention, whereas active attention is referred to as "top-down" or "goal-directed" attention. It has been suggested that visual perception is consisted of three parts, the foveal, parafoveal, and the peripheral vision for which acuity decreases respectively (Liversedge et al., 2011). Since the capacities of the perceptual system are limited, focusing on a certain aspect of the visual field enables us to prioritize relevant information and ignore irrelevant information (Klatt & Memmert, 2021).

Visual selective attention is thought to be both goal directed when attentional priority is given to only those objects and events that are in line with the current goals of the observer; and (2) stimulus-driven when, irrespective of the intentions or goals of the observer, objects and event involuntarily receive attentional priority, a phenomenon referred to as "attentional capture" (Monsell & Driver, 2000). The dwell time of attention in visual search. The movement of attention: it is widely accepted that attention can be shifted from one location to another in the visual field without any concomitant movements of the eyes (Egeth & Yantis, 1997). Several investigators have obtained the results that they took to support the idea that, like a spotlight, attention moves continuously through space (Shulman et al., 1985). Pattern recognition and target detection (Posner & Petersen, 1990).

2.3.8 Relevant gaze heuristics generated through eye-tracking

Eye-trackers reveals many different types of gaze heuristics, allowing for the understanding and interpretation of many cognitive processes (Holmqvist et al., 2011). Among many others, eye-trackers can track traditional eye-tracking metrics ranging from saccades, fixations, pupil dilation, to smooth pursuits, vergence, and tremors (Goldberg & Kotval, 1999).

However, these measures have several limitations when trying to understand deeper insights about cognitive processes and visual scanning strategies in novel interface user interactions. Studies have shown that, traditional metrics do not account for sequential information, thus limiting information about the temporal order, or pattern of visual exploration (Hayes et al., 2011). Additionally, simple metrics cannot reveal participants' cognitive processes, such as information about their intent, nor can they distinguish between exploratory versus focused viewing behaviors. They also do not capture how one's viewing strategy might evolve over time, especially during the course of a visual search task with different stimuli. Finally, traditional metrics experience integration limitations, which reveals little about how different aspects of perception behaviours work together and form insightful patterns that might indicate individuals' cognitive state.

From instructional design (De Bruyne et al., 2024), to visual scanning strategies (Nahlik & Daubenmire, 2022), recent studies in different fields have suggested that advanced eye-tracking methods may provide richer, and more complex information than traditional eye-tracking metrics (Krejtz et al., 2016).

Gaze transition matrix:

Gaze transition matrix (GTM) is a fundamental component in calculating gaze transition entropy (GTE) and analyzing eye movement patterns. It represents the probability distribution of eye movements between predefined Areas of Interest (AOIs) in a visual interface, revealing insights about the randomness or systematicity of scanning patterns. Krejtz et al. (Krejtz et al.,

2015) introduced this method, which consists of first creating a transition matrix that captures the sequential pattern of eye fixations of a participant while performing a task. The core components of the transition matrix structure include:

$$i = Represents\ each\ row\ of\ the\ current\ AOI\ being\ viewed$$

$$j = Represents\ each\ column\ of\ the\ potential\ next\ AOI$$

The formula that allows for the calculation of entropy values is as follows:

$$GTE = -\sum_{i=1}^{n} p_i \sum_{j=1}^{n} p_{ij} log_2 p_{ij}$$
$$i \neq j$$

Where n represents the number of AOIs, and Pi is the simple probability of viewing the ith AOI, pij is the conditional probability of viewing the jth AOI given the previous viewing of the ith AOI (Krejtz et al., 2015). These matrix cells contain transition probabilities (pij) from one AOI to another, which are derived from observed eye movements during task performance. Each fixation sequence is then modeled as a Markov chain, where the state space S consists of all defined AOIs, numbered 1 to s and all transition probabilities (pij) remain constant over time. It is important to note that each transition depends only on the current state, not previous states. The next step involves probabilities calculations, where each cell value (pij) represents the likelihood of the eye moving from AOI i to AOI j, within a specified time interval. The matrix thus allows for the calculation of gaze transition entropy (GTE), a metric used in eye-tracking research to quantitatively describe visual behavior by analyzing the transitions between different areas of interest (AOIs) on a visual display (Krejtz et al., 2015). It is “the rate of fixations transitions between defined spatial regions”, which indicates an overall estimation for the level of complexity or randomness in the patterns of visual scanning relative to stationary entropy.

While considering the overall spatial dispersion of gaze, we can interpret higher entropy being associated with less predictability (Shiferaw et al., 2019). The scanning patterns of individuals can be analyzed with gaze entropy analysis, which allows for the quantification of attention distribution, and the extent of exploration (Krejtz et al., 2015). Calculating transition entropy values for individual subjects’ transition matrices is an approach that allows the measurement of the extent to which the temporal sequence of eye movements is ordered or random during a computer-based task. When applied to eye-tracking data, gaze transition entropy describes the amount of information required to describe the visual strategies followed by a user of a computer application interface.

Previously, GTE has been applied in various domains to analyze group gaze behaviours (Lanini-Maggi et al., 2021). For example, using GTE to compare participants' gaze transitions from viewing paintings from different classical periods helped reveal participants' curiosity and subjective attractiveness can be captured by transition entropy (Krejtz et al., 2015). The optimal range in gaze transition entropy can be considered the ideal level of scanning complexity that results from modulation of the underlying bottom-up influence by top-down prediction, and where gaze transition entropy is expected to increase with greater top-down engagement. Gaze transition and stationary entropy can provide more precise insights into the viewer's state (Shiferaw et al., 2019).

Lower GTE values represent higher systematic and structured scanning patterns, and higher GTE values represent more random and exploratory scanning. Higher transition entropy values denote more randomness and more frequent switching between AOIs. Our modification of Krejtz's method involves using an N-by-N matrix to automatically define AOIs on an interface, which is time saving and allows us to use 36 AOIs to calculate the GTE, providing a more granular analysis.

Attention dispersion (Coefficient K)

Another advanced metric of interest is Coefficient K, first introduced in eye-tracking research by Krejtz et al. (Krejtz, 2016), which serves to distinguish between ambient and focal attention. It is calculated based on the velocity of eye movements, specifically saccades, and the duration of fixations. The coefficient helps identify the type of attention being employed: ambient attention, characterized by faster saccades and shorter fixations, is typically used for scanning a scene, while focal attention, marked by slower saccades and longer fixations, is associated with detailed examination of specific areas of interest. By quantifying these patterns, Coefficient K provides a means to assess the attentional state of an individual, enabling researchers to differentiate between broad, exploratory behavior and more concentrated, focused attention. This

metric has been used in various contexts, such as understanding visual behavior in dynamic environments and in tasks requiring different levels of cognitive load (Krejtz, 2016).
The calculation of coefficient K, involves the transformation of fixation durations (dwells) and saccade amplitudes into a standard score (z-score), allowing computation of an ambient/focal attentional coefficient per individual scan path. More specifically, the transformation of raw data from saccade amplitude and fixation duration into standard scores, representing the distance between the raw score and the mean in standard deviation units, allows for a direct mathematical comparison of both measures. K is derived, through the calculation, for each participant, of the mean difference between standardized values (z-scores) for each saccade amplitude (ai+1) and its preceding ith fixation duration (di):

$$K_i = \frac{d_i - \mu_d}{\sigma_d} - \frac{a_{i+1} - \mu_a}{\sigma_a}$$

$$Such\ that$$

$$K = \frac{1}{n}\sum_{n} K_i$$

The statistical parameters encompass the means (μd, μa) and standard deviations (σd, σa) of fixation durations and saccade amplitudes, respectively, computed across all n fixations recorded during the complete stimulus presentation, resulting in n distinct Ki coefficients over the entire duration of stimuli presentation (Krejtz et al., 2012). Application of the K-coefficient as a parametric scale in eye-tracking research has been used in analyzing eye movement patterns during packaging usability studies, or in visual exploration during website-based task among others(Carbonell et al., 2019; Wals & Wichary, 2023).

Scanpath analysis: Levenshtein distance and scan paths length

According to the Scanpath Theory by Noton and Stark (Noton & Stark, 1971), individuals perceiving a scene store both the scene features and the gaze sequence that was used to inspect that scene. This theory has been supported by many experimental eye-tracking studies, whose results supported the idea that individuals' scanpath patterns were more similar within an individual and between individuals. This evidence supports the hypothesis that internal cognitive structures control not only eye-movements, but also the perception process itself. Using the scanpaths generated by the GTM, it is possible to compare two scanpaths by computing the Levenshtein distance, a string-based that allows for the comparison between two sets of strings (Privitera, 2000).

The discriminative power of this method stems from its ability to map on series of fixations using alphabetic characters (Fahimi & Bruce, 2021). Additionally, using this method will generate Levenshtein distances that will reveal information about group gaze behaviours, such as the length of participants' scanpaths (Davies et al., 2018). The transformation of participants' scanpaths into quantifiable measures involves several sequential steps, based on Davies' method (Davies et al., 2018). First, individual scanpaths are calculated for each subject based on their eye movement recordings, and from these individual trajectories, the average scanpath length is computed per subject to establish their typical viewing pattern. This generates the average scanpath length according to each participant.

To assess individual deviation from group behaviour, which will provide a measure of individual viewing behaviour relative to the group norm, scanpath lengths were aggregated across the entire subject population to derive population-level metrics. Finally, the Levenshtein distance is calculated between each subject's scanpath and the population average, quantifying the degree of dissimilarity between individual and group-level scanning patterns. This method will reveal information about how closely a user's interaction aligns with an optimal path, gauging how learnable an interface is. Altogether these real-time, objective data allows for a quantitative assessment of learnability, offering insights beyond what traditional methods can provide.

Proposed Approach

In this study, we will introduce a novel method of evaluating interface learnability based on Krejtz et al.'s work on gaze transition entropy (2015). The primary objective of this study is to evaluate interface learnability through the analysis of users' gaze heuristics during interaction with novel interfaces. Specifically, we examine gaze transition entropy values generated from automatic Areas of Interest (AOIs) using an N-by-N grid system. This methodology aims to identify specific gaze metrics that correlate with highly learnable interfaces. To validate our approach and provide deeper insights, we tested the following hypotheses:

H1: Participants will exhibit higher k-coefficient values, lower GTE values, and shorter path lengths in the passive conditions than in the active condition.

H2: High task performers, as defined by higher success rates and shorter completion times, will exhibit higher K-coefficient values, shorter path lengths and lower GTE values during their task performance.

2.4 Materials and methods

2.4.1 Participants

Thirty-three participants (aged 19-64, $\overline{x} = 29.30$, $\sigma = 10.50$, 17 males) participated in the current study. Six participants' data were removed due to signal errors, leaving twenty-seven participants at the analysis stage. All participants were recruited via a research panel and were screened-in to be at least 18 years old and not to be susceptible to certain conditions (Epilepsy, astigmatism, cataracts, Lasik surgery or skin sensitivities). Additionally, participants must have had no previous experience with the software that we used for the study. All participants were compensated $30 for their participation in the study.

2.4.2 Ethics statement

The study was approved by the HEC Research Ethics Board (REB) under certificate number 2024-5919. Participants signed an informed consent form prior to the start of the experiment and were informed of their right to stop their participation at any time during the study.

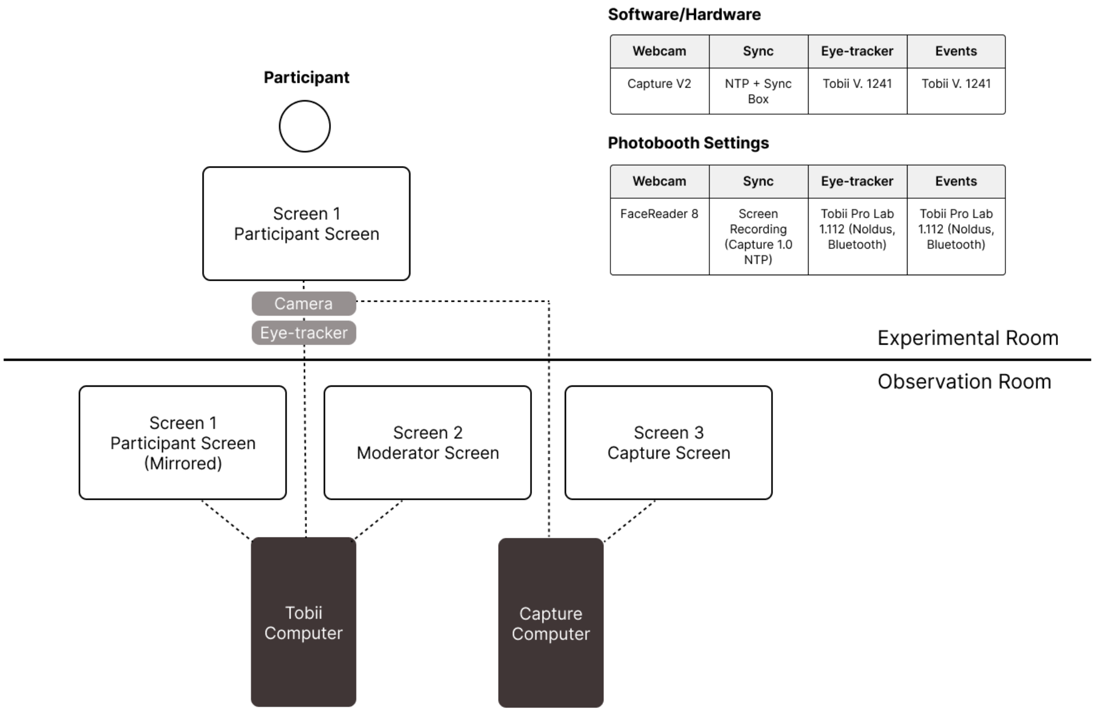
2.4.3 Apparatus and instruments

The study was conducted in an experimental laboratory setting (see figure 2). In the observation room, there were three monitors (23.8-inch HP EliteDisplay E243m with a 1920 x 1080 resolution) that showed respectively, the participant's screen (mirrored), the moderator screen, and the cobalt capture screen. Both participant's and the moderator screen were connected to the

PC that ran the Tobii eye-tracking software, Tobii Pro Lab version 1.241 (Tobii Technology Inc. Stockholm, Sweden), while the cobalt capture screen was connected to the capture PC.

In an adjacent room, the experimental room contained one participant screen that was connected to the Tobii PC. The moderator and research assistants were in the observation room, where the Tobii computer, the moderator screens, and the capture computer were installed. The participant will be in a separate experimental room, where they viewed the stimulus on one screen. One microphone system was connected between the two rooms to allow the moderator to give instructions to the participants. Additionally, participants gaze data was recorded using Tobii Pro Lab (Tobii Technology Inc. Stockholm, Sweden), which was connected with the Tobii Pro Fusion 120 Hz eye-tracker (Tobii Technology Inc. Stockholm, Sweden).

An eye tracker, consisting of cameras, illuminators and algorithms was installed on the participant's screen. The illuminators within the eye tracker create a pattern of near-infrared light on the eyes, while the cameras take high-resolution images of the user's eyes and the patterns. Next, the image processing algorithms find specific details in the user's eyes and reflections patterns. Finally, based on these details, the eyes' position and gaze points are calculated using a sophisticated 3D eye model algorithm (Tobii, 2022). Self-perceived measures of learnability were completed on Qualtrics. Participants' facial expressions were recorded with "Cobalt Capture version 2", using the software Facereader 8.0 (Noldus Information Technology, 2017). This allowed us to gather precise and temporal gaze data. The following synchronization figure shows how the equipment and instruments were connected to ensure valid data synchronization.



Software/Hardware

Webcam	Sync	Eye-tracker	Events
Capture V2	NTP + Sync Box	Tobii V. 1241	Tobii V. 1241

Photobooth Settings

Webcam	Sync	Eye-tracker	Events
FaceReader 8	Screen Recording (Capture 1.0 NTP)	Tobii Pro Lab 1.112 (Noldus, Bluetooth)	Tobii Pro Lab 1.112 (Noldus, Bluetooth)

Figure 2. Study Set-up

2.4.4 Data collection Procedure

Participants were then presented with a consent form that clearly detailed the ensuing study (see Figure 5). Once the participant had consented and agreed to participate in the study, they were guided to the test room, where they proceeded with the calibration of the eye tracker.

Participants were randomly assigned to one of two experimental conditions using counterbalanced task ordering: Condition A (Task 1: Gradient replication task followed by Task 2: Pen tracing task) or Condition B (Task 2: Pen tracing task followed by Task 1: Gradient replication task). This counterbalancing design controlled for potential order effects and ensured equal representation of task sequences across participants. Each task commenced with participants viewing a standardized video tutorial demonstrating the required procedure, after which they were instructed to reproduce the demonstrated technique using the designated software tools.

While both tasks required visual-motor coordination within the same software environment, they differed fundamentally in their attentional demands, subsequently making them ideal for comparing how different eye movement patterns affect viewing outcomes under controlled conditions. During Task 1, the participant was asked to use a color gradient tool to replicate an example design (See Figure 3). The task itself required users to engage in back-and-forth eye movement motions as participants have to repeatedly shift attention between the gradient tool interface, the color selection panels, and the target design area to match chromatic values and spatial distributions to replicate what they saw during the tutorial. During Task 2, the participant was asked to use a pen tracing tool to complete a drawing (See Figure 4). In contrast, this second task required linear eye movement patterns as participants tracked and replicated the actions demonstrated in the video tutorial. Both tasks were performed on the same software, under the same standardized conditions.

Figure 3. Stimuli for task 1

Figure 4. Stimuli for task 2

Following the completion of each task, participants were asked to answer self-reported questions on the perceived learnability of the digital interface on which the task was performed. Participants were allowed to leave at any time with no given reasons. After the completion of both tasks, participants were compensated with an amount of $30.

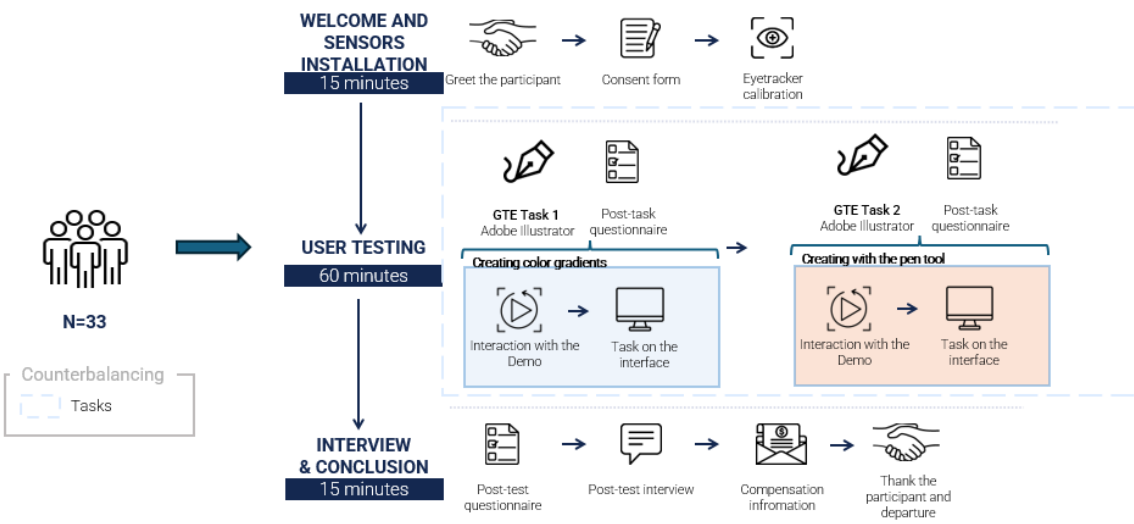


Figure 5. Study Protocol

2.4.5 Statistical analysis

The initial decoding of the eye-tracking data is performed on Python (version 3.7), allowing us to obtain the following data: Gaze transition entropy, K-coefficient, and pupil dilation measurements. Next, the clustering of the gaze paths based on the Levenshtein distances were calculated in R (version 4.3.2). Finally, regular statistical tests were performed on SAS (version 9.4). Due to technical problems with the eye tracking device, the eye tracking data of 7 participants were removed from the analysis. There was a total of 26 valid recordings. Statistical significance was defined at a p-value of below .05.

To study the gaze behaviours of participants across conditions and to ensure the comparability of gaze transition entropy (GTE) across participants and tasks, we normalized the entropy values. Next, we calculated the average transition entropy values and the k-coefficient values of participants in each condition, and across tasks. Additionally, Levenshtein distances were obtained by subtracting the average path lengths of all participants in each condition with each participant. Finally, we extracted participants' scores of the learnability dimension of the SUS according to standard practices and created group averages according to two clusters participant performance: high performers and low performers. Participant performance was determined on the basis of whether or not they succeeded in completing he task and their task completion time.

We tested the effect of engagement condition on gaze heuristics (GTE, K-coefficient, gaze path length, and Levenshtein distance) using Wilcoxon signed-rank tests for paired data. To account for repeated measures, we used mixed-effects linear regression with participants as random effects when modeling the relationship between gaze heuristics and perceived learnability. Mixed-effects logistic regression with random intercepts for participants was applied to binary performance outcomes (success vs. failure), and linear mixed-effects models were used for continuous outcomes such as task time. To account for type I error from multiple comparisons, Bonferroni correction was applied.

2.5 Results

Gaze heuristics among video engagement conditions

Length of the gaze path:

A Wilcoxon signed-rank test was conducted to compare the length of gaze paths in the two video tutorial engagement conditions (see figure 4): passive (M=176.62, SD= 254.111) and active (M=203.096, SD=146.769). The results of the analysis showed that there were no significant differences between the two conditions (p=0.4625, S=28).

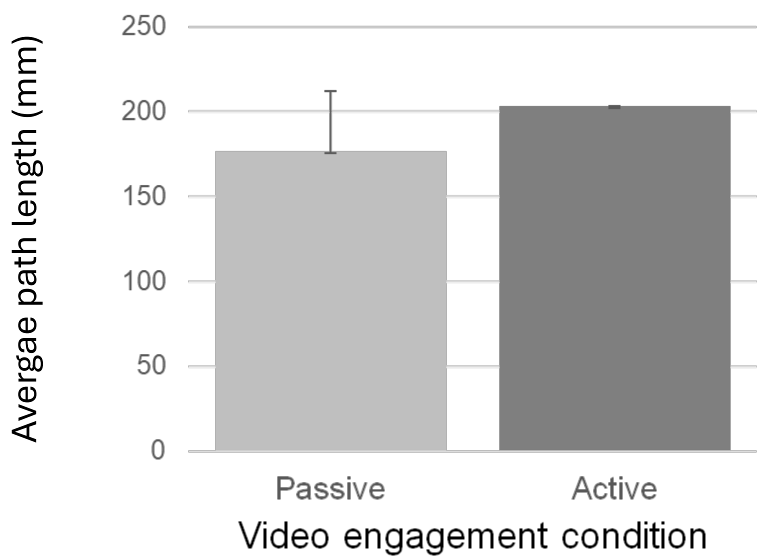


Figure 6. Average gaze path length (mm) according to the video engagement condition during task performance in both tasks.

However, if we were to look at the task level (see figure 5), the length of gaze paths in task 2 were significantly longer in the active condition (p=.003, S= -112) than the passive condition, while there were no significant differences for task 1 (p = .58, S= -22.5).

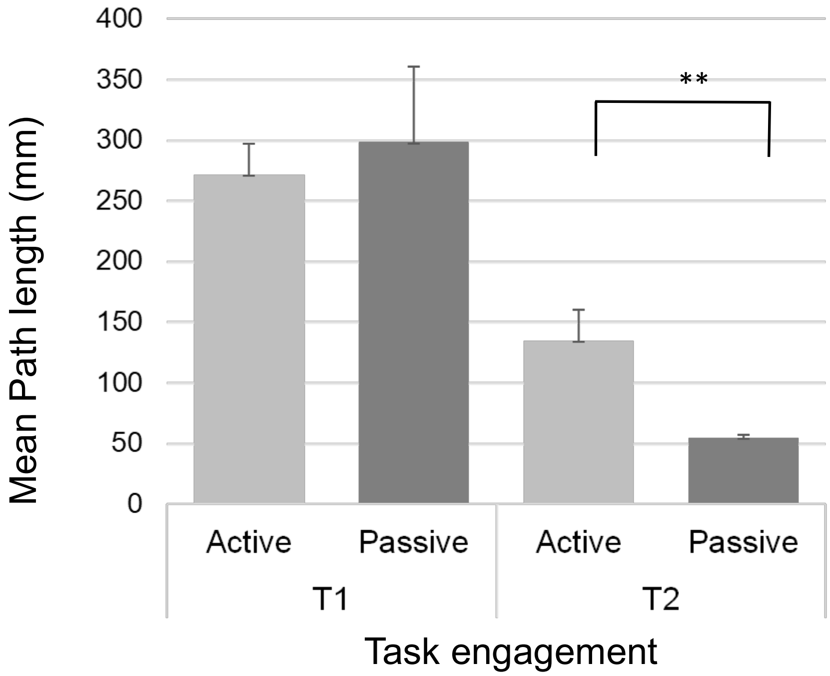


Figure 7. Average path length (mm) according to the video engagement condition by task. Level of significance: * = 0.05; ** = 0.01; *** = <0.001.

Normalized GTE:

A Wilcoxon signed-rank test was conducted to compare the gaze transition entropy of users in the two video tutorial engagement conditions (see figure 6): passive (M=0.42, SD=0.09) and active (M=0.45, SD= 0.09). The result of the analysis showed that there were no significant differences between the two conditions (p=0.1877, S= -52.5).

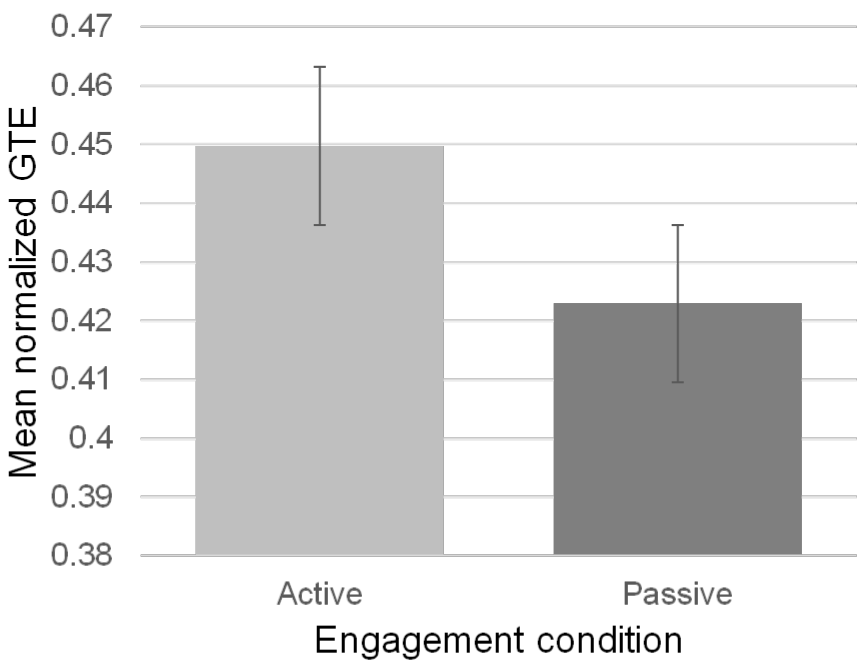


Figure 8. Average normalized gaze entropy values according to the video engagement condition.

More specifically, if we were to look at the task level (see figure 7), the gaze transition entropy of users was significantly higher during the active condition in task 2 ($p=.04$, $S= -78.5$), while there were no significant differences for task 1 ($p = .58$, $S= -22.5$)

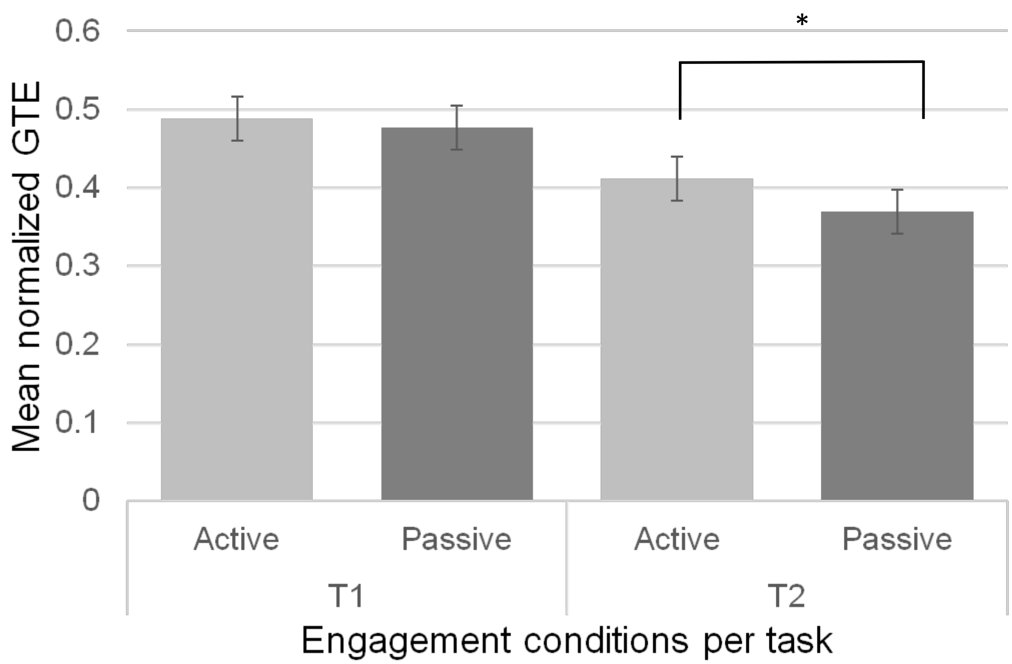


Figure 9. Average normalized gaze transition entropy values according to the video engagement condition. There was a significant difference in task 2 (p=.04). Level of significance: * = 0.05 ** = 0.01 *** = <0.001.

K-coefficient:

A Wilcoxon signed-rank test was conducted to compare the k-coefficient of users in the two video tutorial engagement conditions (see figure 8): passive and active. The k-coefficients of users in the active condition were significantly higher than those in the passive condition, (p=.0017, S= -115.5).

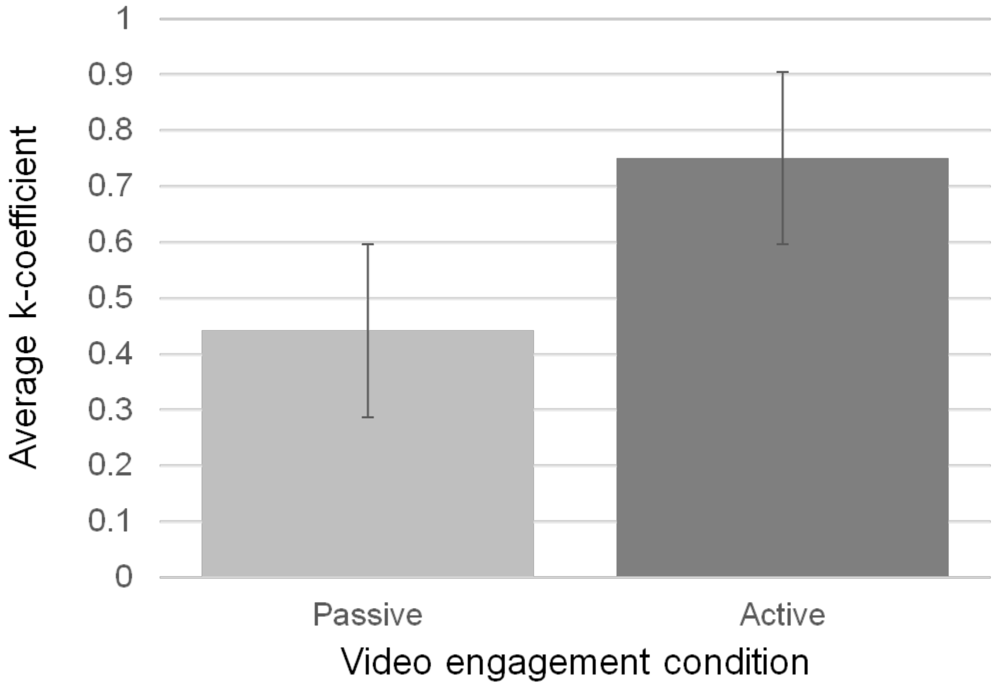


Figure 10. Average k-coefficient values according to the video engagement condition.

More specifically, if we were to look at the task level (see figure 9), k-coefficient of users were significantly higher during the active condition in task 2 ($p=.004$, $S= -106.5$), while there were no significant differences for task 1 ($p = .50$, $S= -27.5$)

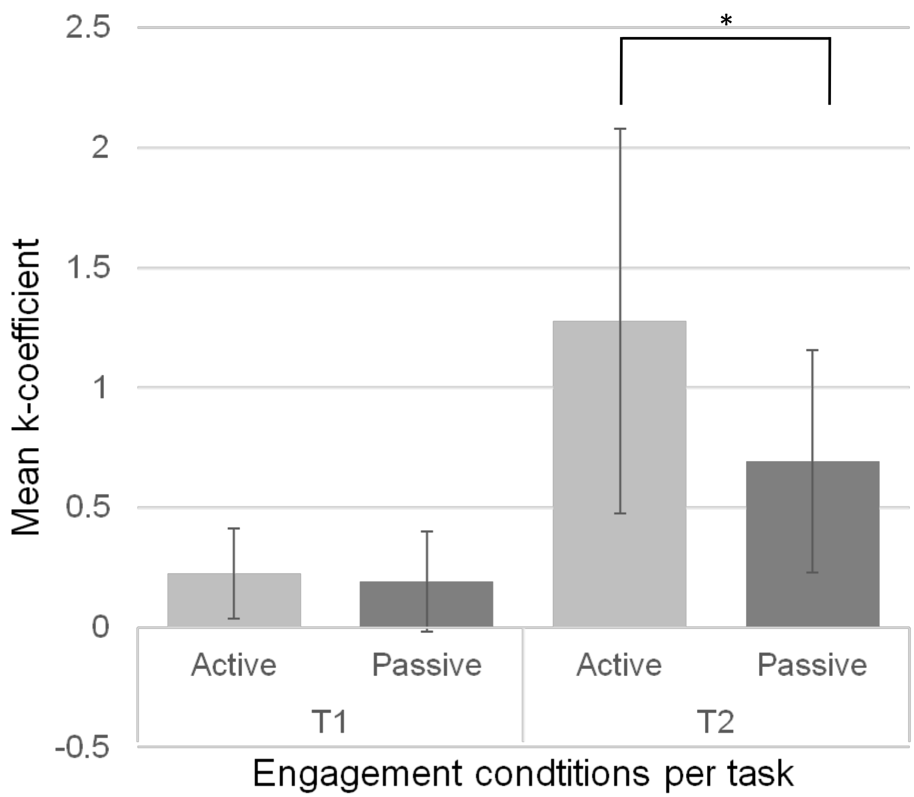


Figure 11. Average k-coefficient values according to the video engagement conditions by task. A significant difference was observed in task 2 (p=.004). Level of significance: * = 0.05 ** = 0.005 *** = <0.001.

Mediators

Cognitive load:

A Wilcoxon signed-rank test was conducted to compare the pupil dilation of users in the two video tutorial engagement conditions: passive and active. The pupil dilation of users in the active condition was significantly greater than those who were in the passive condition (p=<.0001, S=-161.5). This significant difference was replicated in the task level where the pupil dilation of users in the active condition were greater than those in the passive condition for both T1 (p=<.0001, S=-159.5) and T2 (p=<.0001, S=-154.5).

Task Performance Results

K-coefficient and task success rate

A logistic regression was conducted to investigate the effect of k-coefficient on success rates. It was found that higher participants' k-coefficient values were associated with higher success rate (B=2.5346, SE B=1.1126, 95% CI [0.24, 4.83], p = .0158).

Normalized GTE and task success rate

A logistic regression was conducted to investigate the effect of GTE on success rates. It was found that higher GTE values were associated with lower success rate (B=-13.6735, SE B=5.9874, 95% CI [-26.0047, -1.3422], p = .0156).

Path length and task success rate

A logistic regression was conducted to investigate the effect of path length on success rates. It was found that longer path lengths were associated with lower success rate (B=-0.00428, SE B=.001685, 95% CI [-0.00764, -.00092], p = .0066).

Distance and task success rate

A logistic regression was conducted to investigate the effect of Levenshtein distance on success rates. It was found that longer Levenshtein distance were associated with lower success rates (B=-0.00901, SE B=.003005, 95% CI [-0.01520, -0.00282], p = .0030).

Perceived learnability and task success rate

A logistic regression was conducted to investigate the effect of perceived learnability on success rates. It was found that higher perceived learnability scores were associated with lower success rates (B= -0.6467, SE B= .2356, 95% CI [-1.1272, -0.1662], p = .005).

K-coefficient and task completion time

A linear regression was conducted to investigate the effect of k-coefficient on time on task. It was found that higher k-coefficient values were associated with shorter time on task (B= -76.1938, SE B= 23.1181, 95% CI [-123.91, -28.4805], p = .0015).

Normalized GTE and task completion time

A linear regression was conducted to investigate the effect of normalized GTE on time on task. It was found that higher GTE values were associated with longer time on task (B= 824.73, SE B= 156.28, 95% CI [502.18, 1147.27], p = <0.0001).

Path length and task completion time

A linear regression was conducted to investigate the effect of path length on time on task. It was found that longer path lengths were associated with longer time on task (B= .1618, SE B= .03562, 95% CI [.09083, .2327], p= <.0001).

Distance and task completion time

A linear regression was conducted to investigate the effect of Levenshtein distance on time on task. It was found that longer Levenshtein distances were associated with longer time on task (B= .4314, SE B= .06834, 95% CI [.2903, .5724], *p* = <.0001).

Perceived learnability and task completion time

A linear regression was conducted to investigate the effect of perceived learnability on time on task. It was found that higher self-reported perceived learnability scores were associated with longer time on task (B= .0076 SE B= .0013, 95% CI [.005, .0102], *p* = <.0001).

2.6 Discussion

This study examined how participants direct their visual attention and employ scanning strategies while interacting with software, with the goal of identifying gaze metrics that contribute to a learnable interface. Revisiting Schnotz & Bannert's (Schnotz & Bannert, 2003) cognitive model of multimedia learning, the design of the study incorporates notions of cognitive load into task performance on a multimedia platform. The research model was based on the works of works of Krejtz et al. (Krejtz et al., 2015), employing advanced eye metrics to analyze in thirty-three participants across different task scenarios and viewing conditions. The study examined how active versus passive conditions influenced participants' visual attention patterns during interface interaction tasks. Findings revealed that participants in the passive condition exhibited more concentrated gaze patterns, while scanpath lengths remained consistent across conditions. Those in the passive condition also showed reduced focal processing based on k-coefficient values. In the active condition, participants demonstrated more varied visual behavior with higher GTE. Across conditions, high-performing participants across both conditions displayed more efficient visual patterns, characterized by shorter paths, lower Levenshtein distances, higher k-coefficients, and lower GTE. Interestingly, participants who struggled with task performance, as defined by successful task completion and short time on task, reported higher perceived learnability scores.

2.6.1 Video tutorial engagement and gaze heuristics

Passive Condition

Aligned with the hypothesis predicting lower GTE values in the passive condition, the results demonstrated that participants in this condition, who were primarily engaged in observing and processing information, indeed exhibited reduced GTE values. This finding reinforces the notion that passive engagement, characterized by focused observation rather than active task performance, is associated with diminished gaze transitions between elements. These gaze patterns indicate more concentrated and predictable gaze patterns, which are generally associated with better comprehension and a more efficient learning process (Krejtz et al., 2015). This finding is consistent with that of Nahlik & Daubenmire (Nahlik & Daubenmire, 2022), who found that when students carefully scan through chemistry problems are more likely to experience lower transition entropy than instructors, who viewed the problem more randomly. As such, there seems to be an association between the amount of intent one processes visual information, with more intent resulting in lower GTE. However, it is important to note that significant differences were also only observed for task 2 of the study. A possible explanation for this might be due to the nature of the two different tasks. Task 1 required users to engage in back-and-forth eye movement motions to replicate the actions shown in the video tutorial, whereas Task 2 required involved rather linear eye movement motions for the same purpose. Consequently, it is more challenging to distinguish between the active and passive condition within Task 1, due to the chaotic nature of the task stimuli, which might have interfered with the results.

Furthermore, our results suggest that there are not significant differences in participants' scanpath lengths between the active and passive conditions, which align with Scanpath theory, suggesting that individuals store both scene features and the gaze sequence used to inspect that scene when perceiving their environment (Noton & Stark, 1971). Indeed, similarities of scanpaths within individuals validates the notion that each participants' visual patterns are characteristic of individuals themselves due to their unique cognitive mental models. These results reflect previous research that have shown the idiosyncratic nature of scanpaths, based on the assumption that human visual perception is mainly seen as a top-down process, where internal cognitive models control what we perceive rather than external factors (Stark & Choi, 1996).

Contrary to expectations, the k-coefficient values were significantly lower in the passive condition, demonstrating less focal processing than the active condition (Krejtz, 2016). This finding broadly supports the work of other studies in this area linking higher focal processing, characterized by smaller saccades and longer fixations, with visual search behaviours for object recognition (Guo et al., 2022). Since k-coefficient acts as a dynamic indicator of fluctuation between ambient and focal visual scanning, these results capture participants' visual attention in the perception, recognition and identification of complex visual stimuli, the novel interface (Krejtz, 2016).

Active condition

Conversely, those in the active condition, who were engaged in applying what they had learned, demonstrated higher GTE and longer paths, reflecting more exploratory and varied visual behavior as they interacted with the interface (Krejtz et al., 2017). Higher GTE values are associated with disorder, meaning high entropy, will indicate a highly "disordered" visual behavior of a subject. Potentially, this disorder stems from the nature of their gaze patterns, which switches between various AOIs. This suggests that these participants had an unclear understanding of where to focus their attention, not efficiently locating the information that they needed. In contrast, during active task performance, participants displayed higher GTE, reflecting a more exploratory visual behavior necessary for recreating the tutorial content on a new interface. This reflects the findings of previous studies which associated lower average transition entropy with focused attention and high curiosity (Krejtz et al., 2015).

By combining both GTE data and K-coefficient data, it is made possible to infer that that while participants were watching the video tutorial, they were more engaged in focal attention as demonstrated by significantly higher k-coefficient values in the passive condition, as they had to concentrate on the quick adoption of features on the software. As such, it would be relevant to consider a combination of higher k-coefficient values (attentional focus) and lower GTE values (disordered gaze patterns) as an indication of a desirable state in terms of interface learnability.

2.6.2 Task Performance data and Gaze Heuristics

As hypothesized, high performers—defined by higher success rates and shorter task completion times—consistently showed shorter path lengths, lower Levenshtein distances, higher k-coefficient values and lower GTE across both passive and active conditions. This pattern suggests that efficient learners, regardless of their engagement mode, exhibit more focused and structured visual behavior, which aligns with the notion that effective learnability should lead to a rapid and effortless attainment of proficiency.

Specifically, lower GTE and shorter path lengths may be indicative of better learnability, as they reflect more efficient visual processing and attention allocation. Similarly, shorter Levenshtein distances may signify that users are following a more optimal visual path, closely aligning with the intended sequence of interactions, which is a hallmark of a well-designed, learnable interface.

2.6.3 Perceived learnability

The system usability scale (SUS) is a ten-item attitude Likert scale that measures a global view of subjective assessments of usability (Brooke, 1995). More specifically, there are two specific questions of the scale (see figure 10), item 4 and 10, that are considered to be the learnability dimension of the SUS questionnaire (Lewis & Sauro, 2009):

Learnability dimension of the SUS questionnaire
4. I think that I would need the support of a technical person to be able to use this system
10. I needed to learn a lot of things before I could get going with this system

Figure 12. Learnability dimension of the SUS questionnaire, adapted from Brooke (1995).

According to previous research on top-down, or goal-directed attentional processes, it is possible to infer that a proper attentional control allows for efficient task performance (Egeth & Yantis, 1997). In the context of the current study, it was found that higher performers exhibited more focused attentional patterns regardless of which condition they were in. Interestingly, these same high performers reported lower scores on the SUS scale, indicating that they felt they needed less support while interacting with the novel interface. These results align with the results of their eye movement patterns, where participants who successfully completed the task were reported experiencing significantly lower GTE, shorter path lengths, shorter Levenshtein distances, and higher k-coefficient values across tasks. These results mean that these participants' gazes were more predictable, more focused, and they had more efficient visual search patterns overall (Krejtz et al., 2015; Krejtz, 2016).

Altogether, these results demonstrate that participants who had higher attentional control throughout the experiment felt more confident in their ability to use the interface independently. While these results suggest that we cannot directly measure interface learnability using eye-tracking metrics alone, the combination of these behavioural measures and user feedback together can provide nuanced insights into how effectively users are engaging with an interface. These findings highlight the potential of leveraging eye-tracking metrics to advance interface design. By examining the relationship between eye movements, performance, and perceived learnability, designers can create intuitive interfaces that foster natural exploration and reduce reliance on tutorials. Behavioral measures, such as focused attention patterns and efficient visual search behaviors correlate with improved user performance and reduced need for support. This knowledge informs two key applications: designing interfaces that naturally guide users through tasks and developing interactive tutorials that minimize cognitive load. Furthermore, these metrics could enable adaptive interfaces that provide real-time support by detecting user difficulties through gaze patterns and offering tailored assistance, transforming user support into a dynamic and personalized experience.

2.6.4 Cognitive Load

The findings of this study align with the cognitive model of multimedia learning proposed by Schnotz and Bannert (Schnotz & Bannert, 2003), which suggests that effective multimedia learning requires the integration of information from different modalities, such as textual and pictorial, early on in the perceptual process. We based our hypothesis on this theory, which suggests that participants will experience a higher amount of cognitive load during task doing, as they will be concentrating on the task at hand. Although the tasks in this study are strictly not learning tasks, they share similarities with underlying processes that help users become familiar with a new interface. Empirically, while learning refers to the broader, general process of acquiring new knowledge, learnability on the other hand, is a property of an interface that describes how an individual gets acquainted with a system (Nielsen, 1993; Rafique et al., 2012). Our results support this idea, with participants experiencing significantly higher cognitive load during the active engagement condition, where they were asked to replicate the task within the video tutorial.

Cognitive load and perceived learnability

As mentioned previously, users must simultaneously process multiple information streams while managing their cognitive resources when interacting with multimedia interfaces, necessitating effective allocation of their cognitive resources (Schnotz & Bannert, 2003). To recall, our results suggest that cognitive load was significantly higher during the active condition, where participants independently attempted tasks after viewing a tutorial video. According to top-down cognitive processing, perceived learnability is likely related to the alignment between users' expectations that were shaped by the video tutorial and the actual behavior of the system (Egeth & Yantis, 1997; Rai & Callet, 2018). This might explain why successful participants evaluated the system as more learnable when they successfully completed tasks that aligned with their mental models derived from the tutorial. Conversely, misalignments between expected and actual system interactions led to lower perceived learnability.

Cognitive load and eye-tracking metrics

The relationship between cognitive load and perceived learnability is further supported by previously established eye-tracking metrics during task performance and provides additional insights into the cognitive processes of participants during their interaction with the system. During the active condition, participants' focused gaze behaviours, as demonstrated by the higher k-coefficient values might suggest that participants were really concentrated on the task at hand, combined with less spontaneous exploration paired with higher cognitive load can be a sign that they are really concentrated on "getting it right" for their task. However, although they are focused, the higher GTE values indicate more random and less structured visual search patterns, suggesting that they struggled to establish an efficient scanning strategy, supported by a clear mental model of the task requirements since they had never experienced with the interface. This interpretation is supported by the longer scanpath lengths during the active condition, which also reveals more extensive and less efficient visual search patterns. Altogether, these results support the top-down model of information processing based on prior knowledge and expectations (Egeth & Yantis, 1997).

Impact of Research

This study contributes to our understanding of user engagement with interactive media interfaces by providing a nuanced analysis of gaze behavior patterns. The findings reveal that while eye-tracking metrics do not directly measure learnability, they offer valuable behavioral indicators of user performance and interaction with interfaces. These insights underscore the potential for integrating eye-tracking methodologies into comprehensive frameworks for assessing learnability. Such an approach could advance our capacity to evaluate and refine interface designs, ultimately enhancing the overall user experience.

Limitations

Nonetheless, this exploratory study is subject to some limitations that should be considered when interpreting the results. The technical sensitivity of the eye-tracking equipment led to the exclusion of multiple participants from the final analysis due to connection errors, which reduced the overall sample size. This smaller sample may have constrained our ability to detect significant relationships within the data. Additionally, the generalizability of these findings to broader contexts is uncertain, highlighting potential concerns regarding external validity. Future research should aim to address these limitations by implementing more robust technical protocols and expanding participant recruitment, thereby enhancing the reliability and applicability of the findings.

2.7 Conclusion

The current study addressed the possibility of using gaze behaviours to quantify the learnability of an interface. Our results confirmed that while watching a video tutorial, participants experience lower GTE, shorter gaze paths and lower k-coefficient, which is indicative of a focused mode of processing. On the other hand, while performing the task themselves, participants experienced the opposite, which suggests a more exploratory behaviour. While these gaze behaviors show promise as quantitative measures of learnability, further research is needed to refine these metrics and fully understand their implications.

The findings of this study highlight the need for a more nuanced approach to defining and evaluating learnability, considering the complex interplay between different types of gaze behaviours and user engagement modes. The results of this study contribute to the body of literature on eye-tracking, and user experience research and reaffirm the possibility of using empirical methods to assess user experience. By integrating these gaze metrics into usability assessments, researchers and designers can develop more effective strategies for enhancing the learnability of interfaces, thus reducing software onboarding time and reducing technology adoption times. Additionally, our results can also be useful for practitioners and researchers in other fields such as education, human-computer interaction, assistive technology and virtual reality.

References

Baecker, R., Booth, K., Jovicic, S., McGrenere, J., & Moore, G. (2000). *Reducing the gap between what users know and what they need to know* Proceedings on the 2000 conference on Universal Usability, Arlington, Virginia, USA. https://doi.org/10.1145/355460.355467

Bergstrom, J. R., & Schall, A. (2014). *Eye Tracking in User Experience Design*. Morgan Kaufmann Publishers Inc.

Bevan, N., & Macleod, M. (1994). Usability measurement in context. *Behaviour & Information Technology*, *13*(1-2), 132-145. https://doi.org/10.1080/01449299408914592

Beymer, D., & Russell, D. M. (2005). *WebGazeAnalyzer: a system for capturing and analyzing web reading behavior using eye gaze* CHI '05 Extended Abstracts on Human Factors in Computing Systems, Portland, OR, USA. https://doi.org/10.1145/1056808.1057055

Brooke, J. (1995). SUS: A quick and dirty usability scale. *Usability Eval. Ind.*, *189*.

Burr, D. (2011). Visual Perception: More Than Meets the Eye. *Current Biology*, *21*(4), R159-R161. https://doi.org/https://doi.org/10.1016/j.cub.2011.01.007

Butler, K. A. (1985). *Connecting theory and practice: a case study of achieving usability goals* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, San Francisco, California, USA. https://doi.org/10.1145/317456.317472

Carbonell, I., de la Fuente, J., & Afriyie, P. (2019). *Using Mobile Eye Tracking and Coefficient K for Analysing Usability Trials*.

Carroll, J. M., Mack, R. L., Lewis, C. H., Grischkowsky, N. L., & Robertson, S. R. (1985). Exploring Exploring a Word Processor. *Human–Computer Interaction*, *1*(3), 283-307. https://doi.org/10.1207/s15327051hci0103_3

Carter, B. T., & Luke, S. G. (2020). Best practices in eye tracking research. *International Journal of Psychophysiology*, *155*, 49-62. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2020.05.010

Davies, A., Harper, S., Vigo, M., & Jay, C. (2018). Using simultaneous scanpath visualization to investigate the relationship between accuracy and eye movement during medical image interpretation. *J Eye Mov Res*, *10*(5). https://doi.org/10.16910/jemr.10.5.11

Davis, S., & Wiedenbeck, S. (1998). The effect of interaction style and training method on end user learning of software packages. *Interacting with Computers*, *11*(2), 147-172. https://doi.org/10.1016/S0953-5438(98)00026-5

De Bruyne, J., Leersnijder, L., Talsma, D., Demanet, J., Saldien, J., & Bombeke, K. (2024). *Random Gazes, Telling Eyes: Exploring Gaze Transition Entropy as a Performance Indicator in Evaluating Instructional Designs*. https://doi.org/10.54941/ahfe1004747

Dix, A., Finlay, J., Abowd, G., & Beale, R. (2004). Human-Computer Interaction. In.

Duchowski, A. (2007). *Eye Tracking Methodology: Theory and Practice*. https://doi.org/10.1007/978-1-84628-609-4

Eckstein, M. K., Guerra-Carrillo, B., Miller Singley, A. T., & Bunge, S. A. (2017). Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? *Developmental Cognitive Neuroscience*, *25*, 69-91. https://doi.org/https://doi.org/10.1016/j.dcn.2016.11.001

Egeth, H. E., & Yantis, S. (1997). Visual attention: control, representation, and time course. *Annu Rev Psychol*, *48*, 269-297. https://doi.org/10.1146/annurev.psych.48.1.269

Elliott, G. J., Jones, E., & Barker, P. (2002). A grounded theory approach to modelling learnability of hypermedia authoring tools. *Interacting with Computers*, *14*(5), 547-574. https://doi.org/https://doi.org/10.1016/S0953-5438(02)00021-8

Ericsson, K. A., & Simon, H. A. (1984). *Protocol analysis: Verbal reports as data*. The MIT Press.

Fahimi, R., & Bruce, N. D. B. (2021). On metrics for measuring scanpath similarity. *Behavior Research Methods*, *53*(2), 609-628. https://doi.org/10.3758/s13428-020-01441-0

Frey, J., Mühl, C., Lotte, F., & Hachet, M. (2014). *Review of the Use of Electroencephalography as an Evaluation Method for Human-Computer Interaction*.

Gilbert, C. D., & Li, W. (2013). Top-down influences on visual processing. *Nature Reviews Neuroscience*, *14*(5), 350-363. https://doi.org/10.1038/nrn3476

Goldberg, J., & Kotval, X. (1999). Computer interface evaluation using eye movements: Methods and constructs. *International Journal of Industrial Ergonomics*, *24*, 631-645. https://doi.org/10.1016/S0169-8141(98)00068-7

Grondin, S. (2016). *Psychology of Perception* (Vol. 1). Springer Cham.

Grossman, T., Fitzmaurice, G., & Attar, R. (2009). *A survey of software learnability: metrics, methodologies and guidelines* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, MA, USA. https://doi.org/10.1145/1518701.1518803

Guo, Y., Pannasch, S., & Helmert, J. R. (2022). *Eye Movements in Extended Tasks: Analyses of Ambient/Focal Attention with Coefficient K* 2022 Symposium on Eye Tracking Research and Applications, Seattle, WA, USA. https://doi.org/10.1145/3517031.3529630

Hayes, T. R., Petrov, A. A., & Sederberg, P. B. (2011). A novel method for analyzing sequential eye movements reveals strategic influence on Raven's Advanced Progressive Matrices. *Journal of Vision*, *11*(10), 10-10. https://doi.org/10.1167/11.10.10

Hessels, R. S., Kemner, C., van den Boomen, C., & Hooge, I. T. C. (2016). The area-of-interest problem in eyetracking research: A noise-robust solution for face and sparse stimuli. *Behavior Research Methods*, *48*(4), 1694-1712. https://doi.org/10.3758/s13428-015-0676-y

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). Eye Tracking: A Comprehensive Guide To Methods And Measures.

Howes, A., & Young, R. M. (1993). Predicting the learnability of task-action mappings. In *The Soar papers (vol. II): research on integrated intelligence* (pp. 1204–1209). MIT Press.

[ISO], I. O. f. S. (2011). ISO/IEC 25010:2011. In.

[ISO], I. O. f. S. (2023). ISO/IEC 25010:2023. In.

Just, M. A., & Carpenter, P. A. (1976). Eye fixations and cognitive processes. *Cognitive Psychology*, *8*(4), 441-480. https://doi.org/https://doi.org/10.1016/0010-0285(76)90015-3

Kellermann, T., Regenbogen, C., De Vos, M., Mößnang, C., Finkelmeyer, A., & Habel, U. (2012). Effective connectivity of the human cerebellum during visual attention. *J Neurosci*, *32*(33), 11453-11460. https://doi.org/10.1523/jneurosci.0678-12.2012

Klatt, S., & Memmert, D. (2021). Studying Spatial Visual Attention: The Attention-Window Task as a Measurement Tool for the Shape and Maximum Spread of the Attention Window [Original Research]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.614077

Krejtz, I., Szarkowska, A., Krejtz, K., Walczak, A., & Duchowski, A. (2012). Audio description as an aural guide of children's visual attention: Evidence from an eye-tracking study. *Eye*

Tracking Research and Applications Symposium (ETRA). https://doi.org/10.1145/2168556.2168572

Krejtz, K., Çöltekin, A., Duchowski, A., & Niedzielska, A. (2017). Using Coefficient to Distinguish Ambient/Focal Visual Attention During Cartographic Tasks. *J Eye Mov Res*, *10*(2). https://doi.org/10.16910/jemr.10.2.3

Krejtz, K., Duchowski, A., Szmidt, T., Krejtz, I., Perilli, F. G., Pires, A., Vilaro, A., & Villalobos, N. (2015). Gaze Transition Entropy. *ACM Trans. Appl. Percept.*, *13*(1), Article 4. https://doi.org/10.1145/2834121

Krejtz, K., Duchowski, T. A., Krejtz, I., Kopacz, A., & Chrząstowski-Wachtel, P. (2016). Gaze transitions when learning with multimedia. *Journal of Eye Movement Research*, *9*(1). https://doi.org/10.16910/jemr.9.1.5

Krejtz, K. a. D. A. a. K. I. a. S. A. a. K. A. (2016). Discerning Ambient/Focal Attention with Coefficient K. *ACM Trans. Appl. Percept.*, *13*(3). https://doi.org/10.1145/2896452

Lanini-Maggi, S., Ruginski, I. T., Shipley, T. F., Hurter, C., Duchowski, A. T., Briesemeister, B. B., Lee, J., & Fabrikant, S. I. (2021). Assessing how visual search entropy and engagement predict performance in a multiple-objects tracking air traffic control task. *Computers in Human Behavior Reports*, *4*, 100127. https://doi.org/https://doi.org/10.1016/j.chbr.2021.100127

Lewis, J. R., & Sauro, J. (2009, 2009//). The Factor Structure of the System Usability Scale. Human Centered Design, Berlin, Heidelberg.

Lin, H. X., Choong, Y.-Y., & Salvendy, G. (1997). A proposed index of usability: A method for comparing the relative usability of different software systems. *Behaviour & Information Technology*, *16*(4-5), 267-277. https://doi.org/10.1080/014492997119833

Linja-aho, M. (2005). Evaluating and Improving the Learnability of a Building Modeling System. In. Helsinki: University of Technology

Liversedge, S., Gildchrist, I., & Everling, S. (2011). *The Oxford handbook of eye movements* [doi:10.1093/oxfordhb/9780199539789.001.0001]. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199539789.001.0001

Mackamul, E., Casiez, G., & Malacria, S. (2024). Clarifying and differentiating discoverability. *Human–Computer Interaction*, *0*(0), 1-26. https://doi.org/10.1080/07370024.2024.2364606

Marrella, A., & Catarci, T. (2018). *Measuring the Learnability of Interactive Systems Using a Petri Net Based Approach* Proceedings of the 2018 Designing Interactive Systems Conference, Hong Kong, China. https://doi.org/10.1145/3196709.3196744

Michelsen, C. D., Dominick, W. D., & Urban, J. E. (1980). *A methodology for the objective evaluation of the user/system interfaces of the MADAM system using software engineering principles* Proceedings of the 18th annual Southeast regional conference, Tallahassee, Florida. https://doi.org/10.1145/503838.503847

Monsell, S., & Driver, J. (2000). *Control of Cognitive Processes: Attention and Performance XVIII*. https://doi.org/10.7551/mitpress/1481.001.0001

Nahlik, P., & Daubenmire, P. L. (2022). Adapting gaze-transition entropy analysis to compare participants' problem solving approaches for chemistry word problems [10.1039/D2RP00066K]. *Chemistry Education Research and Practice*, *23*(3), 714-724. https://doi.org/10.1039/D2RP00066K

Najemnik, J., & Geisler, W. S. (2005). Optimal eye movement strategies in visual search. *Nature*, *434*(7031), 387-391.

Nguyen, C. T. O., Acosta, M. L., Di Angelantonio, S., & Salt, T. E. (2021). Editorial: Seeing Beyond the Eye: The Brain Connection [Editorial]. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.719717

Nielsen, J. (1993). Chapter 2 - What Is Usability? In J. Nielsen (Ed.), *Usability Engineering* (pp. 23-48). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-08-052029-2.50005-X

Nielsen, J. (1994). *Usability Engineering*. Morgan Kaufmann Publishers Inc.

Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

Noton, D., & Stark, L. (1971). Eye Movements and Visual Perception. *Scientific American*, *224*(6), 34-43. http://www.jstor.org/stable/24922750

Paymans, T. F., Lindenberg, J., & Neerincx, M. (2004). *Usability trade-offs for adaptive user interfaces: ease of use and learnability* Proceedings of the 9th international conference on

Intelligent user interfaces, Funchal, Madeira, Portugal. https://doi.org/10.1145/964442.964512

Poole, A., & Ball, L. (2006). Eye tracking in human-computer interaction and usability research: Current status and future prospects. In (pp. 211-219).

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annu Rev Neurosci*, *13*, 25-42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Privitera, C. M. a. S. L. W. (2000). Algorithms for defining visual regions-of-interest: comparison with eye fixations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(9), 970-982. https://doi.org/10.1109/34.877520

Rafique, I., Weng, J., Abbasi, M., & Lew, P. (2012). *Software Learnability Evaluation An Overview of Definitions and Evaluation Methodologies for GIS Applications*.

Rai, Y., & Callet, P. L. (2018). Chapter 3 - Visual attention, visual salience, and perceived interest in multimedia applications. In R. Chellappa & S. Theodoridis (Eds.), *Academic Press Library in Signal Processing, Volume 6* (pp. 113-161). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-811889-4.00003-8

Rai, Y., & Le Callet, P. (2018). Visual attention, visual salience, and perceived interest in multimedia applications. In *Academic Press Library in Signal Processing, Volume 6* (pp. 113-161). Elsevier. https://hal.science/hal-01970944

Rieman, J. (1996). A field study of exploratory learning strategies. *ACM Trans. Comput.-Hum. Interact.*, *3*(3), 189–218. https://doi.org/10.1145/234526.234527

Santos, P. J., & Badre, A. N. (1995). Discount Learnability Evaluation.

Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction*, *13*, 141-156. https://doi.org/10.1016/S0959-4752(02)00017-8

Shiferaw, B., Downey, L., & Crewther, D. (2019). A review of gaze entropy as a measure of visual scanning efficiency. *Neuroscience & Biobehavioral Reviews*, *96*, 353-366. https://doi.org/https://doi.org/10.1016/j.neubiorev.2018.12.007

Shneiderman, B., Plaisant, C., Cohen, M., & Jacobs, S. (2009). Designing the user interface: strategies for effective human-computerinteraction. *Information Design Journal*, *17*, 157-158. https://doi.org/10.1075/idj.17.2.14mar

Shulman, G. L., Wilson, J., & Sheehy, J. B. (1985). Spatial determinants of the distribution of attention. *Perception & Psychophysics*, *37*, 59-65.

Stark, L. W., & Choi, Y. S. (1996). Experimental metaphysics: The scanpath as an epistemological mechanism. In W. H. Zangemeister, H. S. Stiehl, & C. Freksa (Eds.), *Advances in Psychology* (Vol. 116, pp. 3-69). North-Holland. https://doi.org/https://doi.org/10.1016/S0166-4115(96)80069-0

Stevens, C., & Bavelier, D. (2012). The role of selective attention on academic foundations: a cognitive neuroscience perspective. *Dev Cogn Neurosci*, *2 Suppl 1*(Suppl 1), S30-48. https://doi.org/10.1016/j.dcn.2011.11.001

Stickel, C., Fink, J., & Holzinger, A. (2007, 2007//). Enhancing Universal Access – EEG Based Learnability Assessment. Universal Access in Human-Computer Interaction. Applications and Services, Berlin, Heidelberg.

Tobii, A. (2022). Tobii Pro Lab User Manual (Version 1.241). In. Danderyd, Sweden.

Treue, S. (2003). Visual attention: the where, what, how and why of saliency. *Current Opinion in Neurobiology*, *13*(4), 428-432. https://doi.org/https://doi.org/10.1016/S0959-4388(03)00105-3

Unsöld, M. (2018). Measuring Learnability in Human-Computer Interaction.

Wals, S. F., & Wichary, S. (2023). Under Pressure: Cognitive Effort During Website-Based Task Performance is Associated with Pupil Size, Visual Exploration, and Users' Intention to Recommend. *International Journal of Human–Computer Interaction*, *39*(18), 3504-3515. https://doi.org/10.1080/10447318.2022.2098576

Wolf, C., & Lappe, M. (2021). Vision as oculomotor reward: cognitive contributions to the dynamic control of saccadic eye movements. *Cogn Neurodyn*, *15*(4), 547-568. https://doi.org/10.1007/s11571-020-09661-y

Wong, A. Y., Bryck, R. L., Baker, R. S., Hutt, S., & Mills, C. (2023). *Using a Webcam Based Eye-tracker to Understand Students' Thought Patterns and Reading Behaviors in Neurodivergent Classrooms* LAK23: 13th International Learning Analytics and Knowledge Conference, Arlington, TX, USA. https://doi.org/10.1145/3576050.3576115

World Bank. (2024). Digital Progress and Trends Report 2023. In. Washington.

Yarbus, A. L. (2013). *Eye movements and vision*. Springer.

Zakiniaeiz, Y. (2016). The Mind's Machine: Foundations of Brain and Behavior, Second Edition. In *Yale J Biol Med* (Vol. 89, pp. 110). Copyright ©2016, Yale Journal of Biology and Medicine.

Chapter 3: Managerial article

"Through the User's Eyes: What Eye-tracking Reveals About Better Interface Design"

Summary: As businesses race toward digital transformation, the importance of intuitive interface design has never been greater. This article will introduce a study that uses eye-tracking technology to unveil crucial insights into how humans naturally interact with digital interfaces. The implications extend beyond corporate settings. As technology becomes increasingly more present to our daily lives, these findings could revolutionize how we design interfaces for everyone, from young professionals to aging populations. The results of the study suggest a shift to interfaces that encourage natural exploration while minimizing error. By designing systems that work with, rather than against, our innate visual processing patterns, organizations can create more accessible, efficient, and user-friendly digital environments.

3.1 Why User Experience Makes or Breaks Digital Transformation (Introduction)

Digital transformation is fundamentally reshaping how businesses operate, with organizations increasingly adopting digital systems to streamline workflows and drive operational efficiency (World Bank, 2024). This technological revolution promises significant benefits, from cost savings to enhanced productivity, as companies adapt to an increasingly digital marketplace.

However, amid this rapid transformation, a critical success factor often remains overlooked: user adoption (Taherdoost, 2018). While organizations invest substantially in cutting-edge digital solutions, the reality is that not all systems are intuitive to navigate, creating a significant impact on training requirements and change management strategies. Complex interfaces and inadequate training programs can lead to concerning outcomes: reduced productivity, escalating user frustration, and in worst-case scenarios, complete system abandonment (Gellatly & Gu, 2024).

Therefore, the key to successful digital transformation lies not just in implementing new technologies, but in ensuring their learnability through intuitive interface design and comprehensive training programs. By prioritizing the user experience, organizations can better guarantee the adoption of their digital investments and secure the promised benefits of their transformation initiatives.

3.2 Tracking Glances: How Gaze Patterns Analysis Reveal About Interface Learnability (The Research)

To address these challenges, we turned to advanced eye-tracking technology to decode the fundamental question plaguing digital transformation efforts: What makes an interface truly intuitive? Eye-tracking technology captures where, when, and how users look at an interface, revealing patterns in their gaze and areas that attract attention or cause confusion (Schall & Romano Bergstrom, 2014). By analyzing these gaze behaviors, it is possible to uncover insights about user behavior when interacting with a new interface.

Thus, our study explored the factors that play a key role in interface learnability, from user attention to human cognitive processes. We studied the gaze movements of 33 participants using cutting-edge eye-tracking tools in a controlled laboratory setting.

3.3 Lessons from Gaze Analysis: Translating Insights into Interface Design

Our research generated these evidence-based approaches in the design of a good user interface:

<u>Discovery 101: Scaffolded Exploration:</u>

Allow users to immerse themselves within the interface, allowing them to explore and discover the features with minimal mistakes. How to achieve that? By incorporating elements such as visual aids—think arrows, guiding lines, flashing icons, allow users to understand where to look, while maintaining a sense of control over the interface. For example, it would be relevant to incorporate eye-trackers in the design of interfaces, to determine when and where to incorporate tooltips that might appear when users' gaze linger on complex features. Another good rule would be to create visual hierarchies that will match users' natural scanning patterns.

<u>Make it flexible: Considering different users</u>

The study also suggests that some people might not require as much help as others, considering they might have had prior experience with similar systems, or they are just in general more comfortable with technology. Considering this information, it will be wise to not offer unnecessary support for those who do not need it, by for example, allowing users to turn off help or slightly reduce the intensity of the help.

During users' initial experience, companies could offer a full guide by default, while simultaneously present clear opt-out options for those who might not need it, setting expectations about available support levels. It would also be relevant to offer different configurable versions of the interface, that would be adjustable according to the expertise level, and the type of tasks users would need to accomplish on the interface.

Lessons from this study: Main takeaways for practitioners

Eye-tracking technologies have the potential to offer a direct view into the brain and how we process the information around us. After all, our eyes are what allows us to observe information and process it. Therefore, user perception is also important in the consideration of interface design. The system could be easy to use, but if it looks complicated it can also defeat the user.

Our results suggest that we should start looking beyond the traditional success metrics like error rates, time on task, and start incorporating more advanced practices into the field of user experience. Attention is something that is crucial during interface design. Knowing what are the elements that can capture users' attention is important. Therefore, incorporating this tool in the design of user interface can be a wise decision.

3.4 Conclusion

Designing intuitive interfaces is not just about user experience, it's about future-proofing your digital strategy. Consider Apple's new gaze-control feature, it exemplifies how thoughtful design using eye-tracking technology can drive innovation and inclusivity. Embracing new tools will not only advance inclusivity, but also ensure that organizations remain flexible and adaptable.

The implications ripple far beyond the world of tech. Across sectors, every industry that requires users to engage with new systems, from aviation to healthcare to finance, stands to gain from interfaces that adapt to users' needs. As digital transformation accelerates, the demand for accessible, learnable systems is only growing. Thus, learnable design is not just a technological advantage, it is a strategic imperative for the future.

References

Gettatly, G., & Gu, W. (2024). Understanding Canada's innovation paradox: exploring linkages between innovation, technology adoption and productivity, Economic and social reports, 2563-8955 ; Vol. 4, no. 7, July 2024

Schall, A., & Romano Bergstrom, J. (2014). 1 - Introduction to Eye Tracking. In J. Romano Bergstrom & A. J. Schall (Eds.), *Eye Tracking in User Experience Design* (pp. 3-26). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-408138-3.00001-7

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960-967. https://doi.org/https://doi.org/10.1016/j.promfg.2018.03.137

World Bank. (2024). Digital Progress and Trends Report 2023. In. Washington.

Chapter 4: Conclusion

This exploratory study aimed to develop a method to objectively assess interface learnability. More specifically, the objective was to establish objective indicators of interface learnability by focusing on eye-tracking metrics, particularly gaze patterns, and pupil sizes, as well as task performance. Thirty-three participants participated in a controlled laboratory study that aimed to uncover the gaze behavior of users using eye-tracking technology. Through an approach that integrated gaze data, performance metrics and psychometrics assessments, we aimed to bridge the gap between interface design and a better user experience. This concluding chapter examines the methodological approach used to derive key findings, exploring practical implications, theoretical contributions, and the limits and future avenues of this research.

4.1 Methodological Approach

In the domain of attentional behavior in computer tasks, eye tracking has emerged as the primary method for recording user interactions with computer interfaces. While traditional approaches rely on manually defined Areas of Interest (AOIs), our research introduces an innovative solution based on gaze transition matrices, gaze transition entropy (GTE), and attentional focus dispersion. We proposed a modification of Krejtz et al.'s (2015) approach by developing an automatic AOI generation method that dynamically divides the interface into an N×N grid of coordinates. This approach eliminates the manual AOI definition stage, allowing for a more flexible and adaptable analysis across different interface formats. More specifically, the N×N matrix of dynamically allocated AOIs by taking the screen's full resolution, dividing it into a grid, assigning a unique identifier to each grid square, and creating a comprehensive gaze transition matrix. By automatically customizing the number of AOIs to match the specific interface, our approach enables a more granular and precise analysis of participants' gaze behaviors, offering a significant methodological advancement in eye-tracking research.

4.2 Key Findings

Our results suggest that participants in the passive video viewing state exhibited concentrated, and predictable gaze patterns, characteristic of better comprehension and more efficient information processing. On the other hand, participants during active task performance demonstrated disordered, yet highly focused gaze patterns, suggesting exploratory visual behaviours in the context of applying what they had just learned previously in the video tutorial.

High performers—defined by higher success rates and shorter task completion times—consistently exhibited more focused and structured visual search strategies across both passive and active conditions. This systematic visual behavior pattern provides evidence that effective interface learnability is fundamentally characterized by cognitive efficiency, effective attentional allocation, and adaptable information processing strategies. It would also be relevant to highlight those high performers also rated interface learnability higher, suggesting a relationship between participants' cognition and their performance. However, it might also be the case that subjective complexity perception influenced the rating of the learnability of an interface, regardless of the participants' performance. This entails that failed participants might have interpreted their failure as inherent system complexity, externalizing failure by rating the interface as complex rather than acknowledging personal limitations.

Our findings also align with Schnotz & Bannert's cognitive model of multimedia learning (2003), who stipulated that continuous and systematic switching between different learning material modalities require high working memory resources, suggesting higher cognitive efforts. In fact, higher average cognitive efforts were related to lower average interface learnability ratings, suggesting an inverse relationship between cognitive load and perceived learnability. This inverse relationship suggests that interfaces requiring substantial attentional resources and complex information processing strategies are perceived as less learnable, even when successfully navigated.

4.3 Theoretical Contributions & Practical Implications

This study contributes to the body of work on visual behavior data processing to understand eye-tracking data. By providing a way to quantify learnability through real-time eye-tracking data, this study offers a novel approach to understanding how users interact with and learn from digital interfaces. This contributes to a more precise and objective understanding of learnability, allowing researchers to capture nuances of user behaviour.

For industry practitioners, the results of this study demonstrate how eye-tracking can be a valuable tool to provide insights into how interface design can be optimized to enhance learnability. This will reduce the need for extensive user training and can lead to faster adoption of new systems, ultimately saving time and resources, while improving key performance indicators (KPIs). This study introduces several methodological innovations that can benefit future research. Firstly, the integration of eye-tracking metrics with traditional performance-based measures provides a more comprehensive approach to evaluating learnability. The use of GTE, Coefficient K, and Levenshtein distance in combination offers a multi-dimensional view of user interaction, capturing not only the outcomes but also the underlying cognitive processes involved in learning an interface. Eye movements can also be captured and used as control signals to enable people to interact with interfaces directly without the need for mouse or keyboard input, which can be a major advantage for certain populations of users such as disabled individuals (Poole & Ball, 2006).

4.4 Limitations and Future Research

This research is not without limitations. The relationship between perceived complexity, cognitive load, and interface learnability remains underexplored, leaving room for future investigations to establish how these dimensions interact. Additionally, the size and density of AOIs significantly shape the interpretation of entropy measures, influencing the granularity of visual transitions. This might have influenced the sensitivity of Coefficient K, particularly in dynamic contexts such as motion pictures, requiring further scrutiny. Future research could adopt a multi-modal approach, combining eye-tracking data with complementary physiological measures, to capture a richer understanding of cognitive load and emotional responses during learning. Another interesting avenue to explore are longitudinal studies, that may further illuminate how gaze behaviors evolve across various stages of software mastery, while expanding the application of these methods to diverse contexts, including mobile interfaces, augmented reality, and virtual reality environments. By addressing these gaps, future studies could contribute to a more holistic and nuanced understanding of learnability, advancing both theoretical insights and practical applications in human-computer interaction.

Bibliography

Andrews, T. J., & Coppola, D. M. (1999). Idiosyncratic characteristics of saccadic eye movements when viewing different visual environments. *Vision Research*, *39*(17), 2947-2953. https://doi.org/https://doi.org/10.1016/S0042-6989(99)00019-X

Asan, O., & Yang, Y. (2015). Using Eye Trackers for Usability Evaluation of Health Information Technology: A Systematic Literature Review. *JMIR Hum Factors*, *2*(1), e5. https://doi.org/10.2196/humanfactors.4062

Baecker, R., Booth, K., Jovicic, S., McGrenere, J., & Moore, G. (2000). *Reducing the gap between what users know and what they need to know* Proceedings on the 2000 conference on Universal Usability, Arlington, Virginia, USA. https://doi.org/10.1145/355460.355467

Bergstrom, J. R., & Schall, A. (2014). *Eye Tracking in User Experience Design*. Morgan Kaufmann Publishers Inc.

Bevan, N., & Macleod, M. (1994). Usability measurement in context. *Behaviour & Information Technology*, *13*(1-2), 132-145. https://doi.org/10.1080/01449299408914592

Burr, D. (2011). Visual Perception: More Than Meets the Eye. *Current Biology*, *21*(4), R159-R161. https://doi.org/https://doi.org/10.1016/j.cub.2011.01.007

Butler, K. A. (1985). *Connecting theory and practice: a case study of achieving usability goals* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, San Francisco, California, USA. https://doi.org/10.1145/317456.317472

Carroll, J. M., Mack, R. L., Lewis, C. H., Grischkowsky, N. L., & Robertson, S. R. (1985). Exploring Exploring a Word Processor. *Human–Computer Interaction*, *1*(3), 283-307. https://doi.org/10.1207/s15327051hci0103_3

Carter, B. T., & Luke, S. G. (2020). Best practices in eye tracking research. *International Journal of Psychophysiology*, *155*, 49-62. https://doi.org/https://doi.org/10.1016/j.ijpsycho.2020.05.010

Davies, A., Harper, S., Vigo, M., & Jay, C. (2018). Using simultaneous scanpath visualization to investigate the relationship between accuracy and eye movement during medical image interpretation. *J Eye Mov Res*, *10*(5). https://doi.org/10.16910/jemr.10.5.11

Davis, S., & Wiedenbeck, S. (1998). The effect of interaction style and training method on end user learning of software packages. *Interacting with Computers*, *11*(2), 147-172. https://doi.org/10.1016/S0953-5438(98)00026-5

De Bruyne, J., Leersnijder, L., Talsma, D., Demanet, J., Saldien, J., & Bombeke, K. (2024). *Random Gazes, Telling Eyes: Exploring Gaze Transition Entropy as a Performance Indicator in Evaluating Instructional Designs*. https://doi.org/10.54941/ahfe1004747

Eckstein, M. K., Guerra-Carrillo, B., Miller Singley, A. T., & Bunge, S. A. (2017). Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? *Developmental Cognitive Neuroscience*, *25*, 69-91. https://doi.org/https://doi.org/10.1016/j.dcn.2016.11.001

Egeth, H. E., & Yantis, S. (1997). Visual attention: control, representation, and time course. *Annu Rev Psychol*, *48*, 269-297. https://doi.org/10.1146/annurev.psych.48.1.269

Elliott, G. J., Jones, E., & Barker, P. (2002). A grounded theory approach to modelling learnability of hypermedia authoring tools. *Interacting with Computers*, *14*(5), 547-574. https://doi.org/https://doi.org/10.1016/S0953-5438(02)00021-8

Ericsson, K. A., & Simon, H. A. (1984). *Protocol analysis: Verbal reports as data*. The MIT Press.

Fahimi, R., & Bruce, N. D. B. (2021). On metrics for measuring scanpath similarity. *Behavior Research Methods*, *53*(2), 609-628. https://doi.org/10.3758/s13428-020-01441-0

Gettatly, G., & Gu, W. (2024). Understanding Canada's innovation paradox: exploring linkages between innovation, technology adoption and productivity, Economic and social reports, 2563-8955 ; Vol. 4, no. 7, July 2024

Gilbert, C. D., & Li, W. (2013). Top-down influences on visual processing. *Nature Reviews Neuroscience*, *14*(5), 350-363. https://doi.org/10.1038/nrn3476

Goldberg, J., & Kotval, X. (1999). Computer interface evaluation using eye movements: Methods and constructs. *International Journal of Industrial Ergonomics*, *24*, 631-645. https://doi.org/10.1016/S0169-8141(98)00068-7

Grondin, S. (2016). *Psychology of Perception* (Vol. 1). Springer Cham.

Grossman, T., Fitzmaurice, G., & Attar, R. (2009). *A survey of software learnability: metrics, methodologies and guidelines* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, MA, USA. https://doi.org/10.1145/1518701.1518803

Guo, Y., Pannasch, S., & Helmert, J. R. (2022). *Eye Movements in Extended Tasks: Analyses of Ambient/Focal Attention with Coefficient K* 2022 Symposium on Eye Tracking Research and Applications, Seattle, WA, USA. https://doi.org/10.1145/3517031.3529630

Hayes, T. R., Petrov, A. A., & Sederberg, P. B. (2011). A novel method for analyzing sequential eye movements reveals strategic influence on Raven's Advanced Progressive Matrices. *Journal of Vision*, *11*(10), 10-10. https://doi.org/10.1167/11.10.10

Hessels, R. S., Kemner, C., van den Boomen, C., & Hooge, I. T. C. (2016). The area-of-interest problem in eyetracking research: A noise-robust solution for face and sparse stimuli. *Behavior Research Methods*, *48*(4), 1694-1712. https://doi.org/10.3758/s13428-015-0676-y

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). Eye Tracking: A Comprehensive Guide To Methods And Measures.

Howes, A., & Young, R. M. (1993). Predicting the learnability of task-action mappings. In *The Soar papers (vol. II): research on integrated intelligence* (pp. 1204–1209). MIT Press.

Just, M. A., & Carpenter, P. A. (1976). Eye fixations and cognitive processes. *Cognitive Psychology*, *8*(4), 441-480. https://doi.org/https://doi.org/10.1016/0010-0285(76)90015-3

Klatt, S., & Memmert, D. (2021). Studying Spatial Visual Attention: The Attention-Window Task as a Measurement Tool for the Shape and Maximum Spread of the Attention Window [Original Research]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.614077

Krejtz, I., Szarkowska, A., Krejtz, K., Walczak, A., & Duchowski, A. (2012). Audio description as an aural guide of children's visual attention: Evidence from an eye-tracking study. *Eye Tracking Research and Applications Symposium (ETRA)*. https://doi.org/10.1145/2168556.2168572

Krejtz, K., Duchowski, A., Szmidt, T., Krejtz, I., Perilli, F. G., Pires, A.,…Villalobos, N. (2015). Gaze Transition Entropy. *ACM Trans. Appl. Percept.*, *13*(1), Article 4. https://doi.org/10.1145/2834121

Krejtz, K., Duchowski, T. A., Krejtz, I., Kopacz, A., & Chrząstowski-Wachtel, P. (2016). Gaze transitions when learning with multimedia. *Journal of Eye Movement Research*, *9*(1). https://doi.org/10.16910/jemr.9.1.5

Krejtz, K., Çöltekin, A., Duchowski, A., & Niedzielska, A. (2017). Using Coefficient to Distinguish Ambient/Focal Visual Attention During Cartographic Tasks. *J Eye Mov Res*, *10*(2). https://doi.org/10.16910/jemr.10.2.3

Krejtz, K. a. D. A. a. K. I. a. S. A. a. K. A. (2016). Discerning Ambient/Focal Attention with Coefficient K. *ACM Trans. Appl. Percept.*, *13*(3). https://doi.org/10.1145/2896452

Lanini-Maggi, S., Ruginski, I. T., Shipley, T. F., Hurter, C., Duchowski, A. T., Briesemeister, B. B.,…Fabrikant, S. I. (2021). Assessing how visual search entropy and engagement predict performance in a multiple-objects tracking air traffic control task. *Computers in Human Behavior Reports*, *4*, 100127. https://doi.org/https://doi.org/10.1016/j.chbr.2021.100127

Lin, H. X., Choong, Y.-Y., & Salvendy, G. (1997). A proposed index of usability: A method for comparing the relative usability of different software systems. *Behaviour & Information Technology*, *16*(4-5), 267-277. https://doi.org/10.1080/014492997119833

Linja-aho, M. (2005). Evaluating and Improving the Learnability of a Building Modeling System. In. Helsinki: University of Technology

Liversedge, S., Gildchrist, I., & Everling, S. (2011). *The Oxford handbook of eye movements* [doi:10.1093/oxfordhb/9780199539789.001.0001]. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199539789.001.0001

Mackamul, E., Casiez, G., & Malacria, S. (2024). Clarifying and differentiating discoverability. *Human–Computer Interaction*, *0*(0), 1-26. https://doi.org/10.1080/07370024.2024.2364606

Marrella, A., & Catarci, T. (2018). *Measuring the Learnability of Interactive Systems Using a Petri Net Based Approach* Proceedings of the 2018 Designing Interactive Systems Conference, Hong Kong, China. https://doi.org/10.1145/3196709.3196744

Michelsen, C. D., Dominick, W. D., & Urban, J. E. (1980). *A methodology for the objective evaluation of the user/system interfaces of the MADAM system using software* *engineering principles* Proceedings of the 18th annual Southeast regional conference, Tallahassee, Florida. https://doi.org/10.1145/503838.503847

Molina, A. I., Arroyo, Y., Lacave, C., Redondo, M. A., Bravo, C., & Ortega, M. (2024). Eye tracking-based evaluation of accessible and usable interactive systems: tool set of guidelines and methodological issues. *Universal Access in the Information Society*. https://doi.org/10.1007/s10209-023-01083-x

Monsell, S., & Driver, J. (2000). *Control of Cognitive Processes: Attention and Performance XVIII*. https://doi.org/10.7551/mitpress/1481.001.0001

Nahlik, P., & Daubenmire, P. L. (2022). Adapting gaze-transition entropy analysis to compare participants' problem solving approaches for chemistry word problems [10.1039/D2RP00066K]. *Chemistry Education Research and Practice*, *23*(3), 714-724. https://doi.org/10.1039/D2RP00066K

Nguyen, C. T. O., Acosta, M. L., Di Angelantonio, S., & Salt, T. E. (2021). Editorial: Seeing Beyond the Eye: The Brain Connection [Editorial]. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.719717

Nielsen, J. (1993). Chapter 2 - What Is Usability? In J. Nielsen (Ed.), *Usability Engineering* (pp. 23-48). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-08-052029-2.50005-X

Nielsen, J. (1994). *Usability Engineering*. Morgan Kaufmann Publishers Inc.

Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

Noton, D., & Stark, L. (1971). Eye Movements and Visual Perception. *Scientific American*, *224*(6), 34-43.

Paymans, T. F., Lindenberg, J., & Neerincx, M. (2004). *Usability trade-offs for adaptive user interfaces: ease of use and learnability* Proceedings of the 9th international conference on Intelligent user interfaces, Funchal, Madeira, Portugal. https://doi.org/10.1145/964442.964512

Poole, A., & Ball, L. (2006). Eye tracking in human-computer interaction and usability research: Current status and future prospects. In (pp. 211-219).

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annu Rev Neurosci*, *13*, 25-42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Pressman, R. (2009). *Software Engineering: A Practitioner's Approach* (7 ed.). McGraw-Hill Inc.

Privitera, C. M. a. S. L. W. (2000). Algorithms for defining visual regions-of-interest: comparison with eye fixations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(9), 970-982. https://doi.org/10.1109/34.877520

Rafique, I., Weng, J., Abbasi, M., & Lew, P. (2012). *Software Learnability Evaluation An Overview of Definitions and Evaluation Methodologies for GIS Applications*.

Rai, Y., & Le Callet, P. (2018). Visual attention, visual salience, and perceived interest in multimedia applications. In *Academic Press Library in Signal Processing, Volume 6* (pp. 113-161). Elsevier.

Santos, P. J., & Badre, A. N. (1995). Discount Learnability Evaluation.

Schall, A., & Romano Bergstrom, J. (2014). 1 - Introduction to Eye Tracking. In J. Romano Bergstrom & A. J. Schall (Eds.), *Eye Tracking in User Experience Design* (pp. 3-26). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-408138-3.00001-7

Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction*, *13*, 141-156. https://doi.org/10.1016/S0959-4752(02)00017-8

Shiferaw, B., Downey, L., & Crewther, D. (2019). A review of gaze entropy as a measure of visual scanning efficiency. *Neuroscience & Biobehavioral Reviews*, *96*, 353-366. https://doi.org/https://doi.org/10.1016/j.neubiorev.2018.12.007

Shulman, G. L., Wilson, J., & Sheehy, J. B. (1985). Spatial determinants of the distribution of attention. *Perception & Psychophysics*, *37*, 59-65.

Stark, L. W., & Choi, Y. S. (1996). Experimental metaphysics: The scanpath as an epistemological mechanism. In W. H. Zangemeister, H. S. Stiehl, & C. Freksa (Eds.), *Advances in Psychology* (Vol. 116, pp. 3-69). North-Holland. https://doi.org/https://doi.org/10.1016/S0166-4115(96)80069-0

Stevens, C., & Bavelier, D. (2012). The role of selective attention on academic foundations: a cognitive neuroscience perspective. *Dev Cogn Neurosci*, *2 Suppl 1*(Suppl 1), S30-48. https://doi.org/10.1016/j.dcn.2011.11.001

Stickel, C., Fink, J., & Holzinger, A. (2007, 2007//). Enhancing Universal Access – EEG Based Learnability Assessment. Universal Access in Human-Computer Interaction. Applications and Services, Berlin, Heidelberg.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960-967. https://doi.org/https://doi.org/10.1016/j.promfg.2018.03.137

Tobii, A. (2022). Tobii Pro Lab User Manual (Version 1.241). In. Danderyd, Sweden.

Tullis, T., & Albert, W. (2008). *Measuring the User Experience: Collecting, Analyzing, and Presenting Usability Metrics: Second Edition*.

Unsöld, M. (2018). Measuring Learnability in Human-Computer Interaction.

World Bank. (2024). Digital Progress and Trends Report 2023. In. Washington.

Zakiniaeiz, Y. (2016). The Mind's Machine: Foundations of Brain and Behavior, Second Edition. In *Yale J Biol Med* (Vol. 89, pp. 110). Copyright ©2016, Yale Journal of Biology and Medicine.

Appendices

Appendix A. Research Ethics Certificated Issued by HEC Montreal

HEC MONTRĒAL

Comité d'éthique de la recherche

CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

Projet # : 2024-5919

Titre du projet de recherche : Comparaison des demo d'accompagnements et des outils de FAQ dans la banque numérique : Une étude sur l'efficacité, l'efficience et la charge cognitive

Chercheur principal : Sylvain Sénécal, Professeur titulaire, Marketing, HEC Montréal
Cochercheurs : Pierre-Majorique Léger; Marc Fredette; Constantinos K. Coursaris; Frédérique Bouvier; Juan Fernandez Shaw; Luis Carlos Castiblanco; David Brieugne; Salima Tazi; Xavier Côté; Alexander John Karran; François Courtemanche; Élise Imbeault; Jia Xuan Zheng; Juan Francisco Monroy Guevara; Shang Lin Chen

Date d'approbation du projet : 09 mai 2024
Date d'entrée en vigueur du certificat : 09 mai 2024
Date d'échéance du certificat : 1 mai 2025

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2024-05-09 à 16:11

Appendix B. End of research study attestation Issued by HEC Montreal

HEC MONTRĒAL

Comité d'éthique de la recherche

ATTESTATION D'APPROBATION ÉTHIQUE COMPLÉTÉE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet des approbations en matière d'éthique de la recherche avec des êtres humains nécessaires selon les exigences de HEC Montréal.

La période de validité du certificat d'approbation éthique émis pour ce projet est maintenant terminée. Si vous devez reprendre contact avec les participants ou reprendre une collecte de données pour ce projet, la certification éthique doit être réactivée préalablement. Vous devez alors prendre contact avec le secrétariat du CER de HEC Montréal.

Nom de l'étudiant(e) : Jia Xuan Zheng

Titre du projet supervisé/mémoire/thèse : An Implementation of Gaze Analytic Methods to Evaluate User Performance and Interface Learnability

Titre du projet sur le certificat : Comparaison des demo d'accompagnements et des outils de FAQ dans la banque numérique : Une étude sur l'efficacité, l'efficience et la charge cognitive

Projet # : 2024-5919

Chercheur principal / directeur de recherche : Sylvain Sénécal

Cochercheurs : Pierre-Majorique Léger; Marc Fredette; Constantinos K. Coursaris; Frédérique Bouvier; Juan Fernandez Shaw; Luis Carlos Castiblanco; David Brieugne; Salima Tazi; Xavier Côté; Alexander John Karran; François Courtemanche; Élise Imbeault; Jia Xuan Zheng; Juan Francisco Monroy Guevara; Shang Lin Chen; Simon Léger

Date d'approbation initiale du projet : 09 mai 2024

Date de fermeture de l'approbation éthique pour l'étudiant(e) : 04 décembre 2024

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2024-12-04 à 14:06

NAGANO www.semiweb.ca Fin de participation d'un étudiant à un projet
Comité d'éthique de la recherche - HEC Montréal 1 / 1

Appendix C. AI Declaration form

Declaration of AI use in thesis

Declaration by: Jia Xuan Zheng

Program of studies: Msc User Experience—Thesis stream

I declare that I have made an agreement with the supervising person or committee for my project regarding how I use generative artificial intelligence to produce the deliverables for my thesis or supervised project. I also promise to renew the agreement if I plan to make any changes.

Stage in the process	Use of generative AI
Research Question	[0% AI]
Literature review	[10% AI] Used generative AI to summarize relevant areas of literature review, and come up with a plan to systematically organize and plan my literature review
Experimental design	[0% AI]
Data Collection	Recruitment of participants [0% AI] Pre-testing and data collection operations management [0% AI] Collecting data [0% AI]
Statistical Analysis	Performing statistical analysis [20% AI] Used generative AI to verify my R program code for data analysis before submitting it for review by the statistician at the Tech3lab, Shang Lin Chen.
Thesis writing	Redaction of thesis and articles [20% AI] Used generative AI to come up with the structure of the thesis and refine the logical flow of paragraphs.

Date of document: February 10, 2025

Jia Xuan Zheng' Signature: