Studying Parallel Coordinates Under Varying Aspect Ratios

Leon Meka[1], Mirjam Kronsteiner[1] and Johanna Schmidt[1,2][a]

[1]*Visual Analytics, VRVis GmbH, Austria*

[2]*Institute of Visual Computing & Human-Centered Technology, TU Wien, Austria*

Keywords: Information Visualization, Parallel Coordinates, Aspect Ratio, Visualization Literacy.

Abstract: In constraint layout environments like dashboards and multi-view applications, designers have less freedom in selecting the correct aspect ratios for plots. Especially for web-based, responsive dashboards, designers have little to no control over the layout and size of the presented plots. The effect of aspect ratios on the readability of line charts and scatter plots has already been studied. However, more evidence is needed for parallel coordinates, where line slopes indicate correlations between variables. This paper presents a first step towards understanding the effect of aspect ratios on the readability of parallel coordinates. We present a statistical analysis of aspect ratio effects and summarize the results of a quantitative user study on user literacy under different aspect ratios. The statistical analysis revealed that angle parameters stay more homogeneous when changing the plot size in case landscape orientation is used. The user study showed that human observers perform well when judging correlation based on the angles under differences between plot width and height.

1 INTRODUCTION

In recent years, dashboard creation has become increasingly popular in data-driven workflows in many applications (Wexler et al., 2017). Dashboards are regularly used in business intelligence (BI) but have also entered other domains like healthcare (Zhuang et al., 2022), infrastructure planning (Matheus et al., 2020), sports (Goudsmit et al., 2022), and the public discourse during the pandemic (Zhang et al., 2023). A dashboard can be defined as a visual display of essential information found in the underlying data to communicate insights. Dashboards enable the efficient handling and interpretation of vast amounts of data and provide quick overviews on one screen without the need to scroll or switch views. Dashboard designers consolidate and arrange numbers, metrics, key performance indicators, and visualizations on a single screen, allowing users to track data points, monitor trends, and make informed decisions quickly. Dashboards may be but are not required to be interactive (Sarikaya et al., 2019). Interactions may involve selections, filtering, design adaptations (e.g., changing color scales), and view customization (e.g., adapting layout and re-arranging views).

When designing data visualizations, designers can rely on existing best practices for visualization design (Midway, 2020). Guidelines usually involve suggestions for color choices, visual encodings, and chart types. Less focus has been put on the size of the plots since, when designing a single visualization, it is easy to use as much space as possible. However, when placing data visualizations inside a dashboard layout, constraints regarding the available space and shape of the visualization apply. Users may also be allowed to change the size and position of views in the dashboard, leading to other visualizations being adapted accordingly. In addition, dashboard applications are increasingly built in a web-based manner to enable easy, cross-platform access where users do not have to install any software. Responsive designs for dashboards ensure that users can view dashboards on devices with varying screen sizes (Zeng et al., 2024). As such, web-based settings give designers less control over the exact layout as it adapts to different screens.

The aspect ratio of a data visualization affects how quickly users can detect trends and patterns in a data visualization (see also Figure 1). The aspect ratio is critical when plotting time series data. In line charts, trends are judged based on the slope of plotted lines, which are greatly affected by the aspect ratio of the graph. As a rule of thumb, researchers already recommended selecting an aspect ratio of a graph by banking line segments of the graphed data to an angle of 45 degrees (known as *banking to 45°*) (Cleveland, 1986).

[a] https://orcid.org/0000-0002-9638-6344

Meka, L., Kronsteiner, M. and Schmidt, J.
Studying Parallel Coordinates Under Varying Aspect Ratios.
DOI: 10.5220/0013379300003912

In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 992-999
ISBN: 978-989-758-728-3; ISSN: 2184-4321

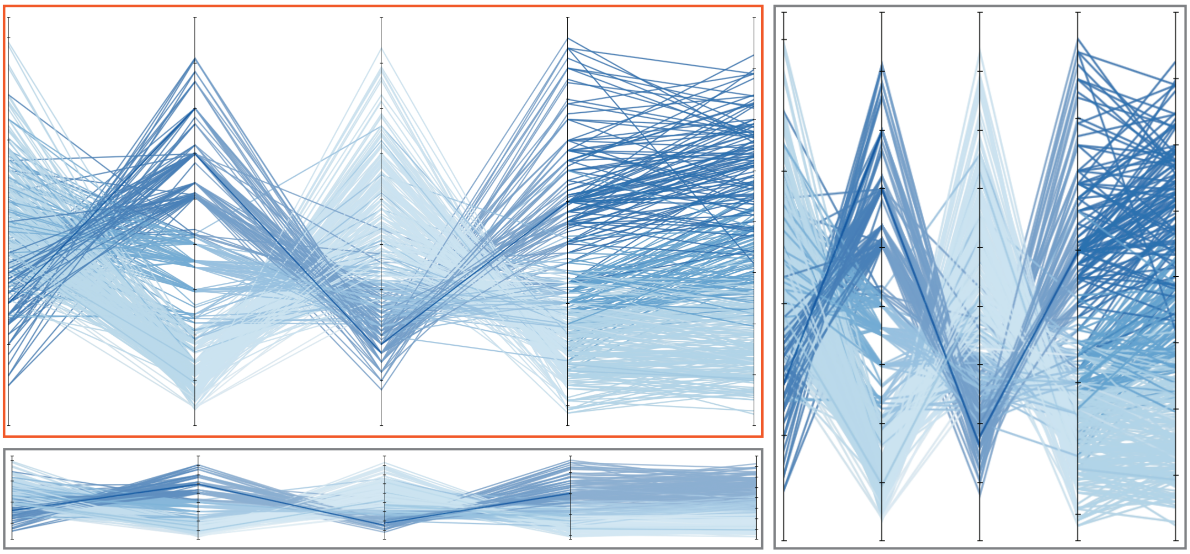

Figure 1: Parallel coordinates plots with different aspect ratios. Line angles are an essential indicator in parallel coordinate plots to show positive or negative correlations between variables and variables without any strong correlations. Usually, parallel coordinates are rendered in a rectangular plot (marked in orange). However, especially in dashboard and multi-view settings, plots may appear in unexpected aspect ratios (marked in gray).

This rule and later variants based on it (Heer and Agrawala, 2006) emphasize the importance of considering aspect ratios when creating a chart, mainly when lines are used as geometric primitives.

Similar to line charts, parallel coordinates plots use lines to depict data values. Due to the point-line duality, data points become polylines when arranging axes in parallel. Line slopes between two axes play an important role in parallel coordinates. The visible line patterns indicate whether we can see a strong positive correlation (parallel lines) or a strong negative correlation (X-shape) between two variables (Ware, 2012). Since angles are an important visual indicator in parallel coordinates, researchers have used line angles to develop matching interaction mechanisms. Angle-dependent selection mechanisms allow to filter lines based on their angles (Hauser et al., 2002) and to select lines based on their slope (Sahann et al., 2021). Line angles and slope guide the user when exploring data in parallel coordinates. The effect on the interpretability of line angles in parallel coordinates under different aspect ratios has yet to be studied. To improve the general understanding in this regard, we

- present a **statistical analysis** of the effect of aspect ratios on parallel coordinate plots,
- summarize the outcomes of a **quantitative user study** targeted to learn more about the users' literacy under different aspect ratios, and
- provide **first guidelines** and ideas for future work.

2 RELATED WORK

Our research addresses the topics of parallel coordinates, dashboard design, and design considerations regarding aspect ratio.

2.1 Parallel Coordinates

Parallel coordinates are a powerful visualization technique for representing multi-dimensional data (Kelleher and Wagener, 1985). Axis, which are arranged in parallel, represent data dimensions and data points are depicted as polylines. Parallel coordinates are widely used in various fields, including engineering (Cibulski et al., 2023), material sciences (Rickman, 2018), and ensemble data (Firat et al., 2023). Johansson and Forsell (Johansson and Forsell, 2016) presented an extensive study on different rendering techniques and evaluated them regarding their usefulness for data analysis. Parallel coordinates offer a variety of research directions (Heinrich and Weiskopf, 2013) for improved rendering (e.g., bundling), solving overplotting, and integrating interaction. A full review of all research results on parallel coordinates, including bundling techniques and axis reordering, goes beyond the scope of this paper. We concentrate on visual structures within and literacy of parallel coordinates plots. Dasgupta and Kosara (Dasgupta and Kosara, 2010) presented a screen-space metrics to evaluate parallel coordinates plots. The metric takes visual structures like the number of line crossings, crossing angles, convergence, overplotting, and other features into account. The best layouting for a plot can be chosen according to this metric. Parallel coordinates literacy (i.e., the ability to read and interpret the plots) has been intensively studied by Firat et al. (Firat et al., 2022). Howe and Purves (Howe and Purves, 2005) studied the perception of angles and oriented lines in images. Johansson et al. (Johansson et al., 2008) studied the ability of humans to perceive patterns in parallel coordinates and concluded that a maximum of 11 variables should be used not to overwhelm users during exploration. Kaur and Karki (Kaur and Karki, 2018) used additional connected views to improve the readability of parallel coordinates. The effect of varying aspect ratios on angle perception in parallel coordinates has not been studied yet. **Our studies contribute new knowledge on angle perception in parallel coordinates under varying aspect ratios.**

2.2 Dashboard Design

Dashboards, also called multiple-view visualizations (Qu and Hullman, 2018), have only lately been identified as an essential aspect to study in visualization research (Sarikaya et al., 2019). Dashboards are already ubiquitously used in different domains, especially business intelligence, but also tourism (Antolini et al., 2024), social media analysis (Lughbi et al., 2024), or healthcare (Zhuang et al., 2022). Designing a dashboard requires the consideration of known guidelines for designing visualizations and layout optimization. Summarized as dashboard design patterns (Bach et al., 2023), designers are provided with design suggestions based on the *genre* their dashboard is settled in. Kristiansen et al. (Kristiansen et al., 2022) provided a *semantic snapping* approach to help novice users complete dashboards based on existing views. Setlur et al. (Setlur et al., 2024) who developed a heuristics for cooperative dashboard design. Conrow et al. (Conrow et al., 2023) proposed a design framework for dashboards for mobility data, which usually contain geospatial information. Epperson et al. (Epperson et al., 2023) suggested a dashboard authoring system where designers do not need to create every visualization individually. Chen et al. (Chen et al., 2021) extracted design patterns from 360 images from previous publications, incorporating the extracted knowledge into a dashboard design recommendation system. *DMiner* (Lin et al., 2024) is another dashboard recommendation system based on 854 dashboards that have been crawled online. Dashboard recommendation systems are useful for many applications where designers may not have a visualization background (Soni et al., 2024). Increasingly, researchers integrated artificial intelligence (AI) tools into the dashboard generation process (Wu et al., 2022). Ma et al. (Ma et al., 2021) proposed a deep-learning-based dashboard authoring system that suggests dashboards based on an image or a sketch. Other AI-based approaches concentrate on user intent (Pandey et al., 2023) or intended insights (Deng et al., 2023) when suggesting dashboard designs. **We contribute new guidelines about how to properly insert a parallel coordinates plot into a dashboard layout, which future dashboard recommendation approaches may consider.**

2.3 Aspect Ratio in Visualization

Design considerations for visualization usually target color scales, shapes, simplicity, and chart types. Guidelines for designing effective data visualization is essential in visualization research not to mislead viewers (McNutt et al., 2020). In their fifth of the ten guidelines for effective data visualization, Kelleher and Wagener (Kelleher and Wagener, 2011) address a carefully chosen aspect ratio as an important design consideration, especially for time series data. The effect of different aspect ratios has been intensively studied for line plots. As a first approach, Cleveland (Cleveland, 1986) suggested the *banking to 45°* approach, where line segments in a line plot should all have an angle of 45 degrees. Further approaches built on this rule and suggested extensions toward considering both axes (Wang et al., 2018), integrating spectral analysis (Heer and Agrawala, 2006), and computing a slope ratio estimation (Talbot et al., 2012). Talbot et al. (Talbot et al., 2011) suggested minimizing the arc length of the data curve in a line plot to find the optimal aspect ratio. Other approaches concentrated on finding an optimal aspect ratio for scatter plots. Fink et al. (Fink et al., 2013) proposed an approach based on Delauney triangulation of the plot. Wang et al. (Wang et al., 2019) used the information from the rendered plot images to compute an optimal aspect ratio. Wei et al. (Wei et al., 2020) concentrate on the users' perception of scatter plots with varying aspect ratios and identify a linear relationship between geometric changes and introduced bias. Ceja et al. (Ceja et al., 2021) studied the effect of changing aspect ratios on bar charts and noticed that wide aspect ratios lead to overestimating bars, and narrow aspect ratios lead to underestimating bars. **We contribute a statistical analysis and results from a quantitative user study on the effect of changing aspect ratios for parallel coordinates.**

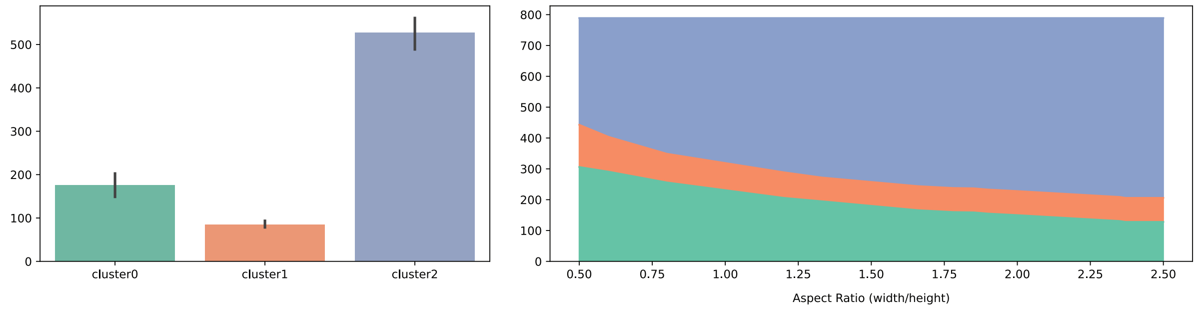

Figure 2: Clustering results. Clustering all plots according to angle parameters revealed three clusters. The plot on the left side shows the cluster sizes and depicts that primarily *cluster2* can be found in the data. The plot on the right side shows the distribution of clusters among different aspect ratios. Larger aspect ratios show less variety in cluster distribution.

3 ANGLES UNDER VARYING ASPECT RATIO

We studied the effect of angles in parallel coordinates under varying aspect ratios from two different directions. As a first step, we collected statistical information on how different aspect ratios affect the distribution of angles (described in Section 3.1). As a second approach, we conducted a user study to learn more about users' perception of angles under varying aspect ratios (described in Section 3.2).

3.1 Statistical Analysis

The statistical analysis aimed to study the distribution of angle parameters under different aspect ratios. We created a web-based application where it was possible to load different datasets (stored as CSV files), display the dataset in a parallel coordinates plot, and change the aspect ratio (either by drag-and-drop or by assigning a specific ratio). Our application also allowed us to calculate the following angle parameters for all lines between all axes: (i) **average** angle, (ii) **minimum** angle, (iii) **maximum** angle, and (iv) **sum** of all angles.

We selected a set of datasets for the study to conduct a statistical analysis (Table 1). We queried Open Source repositories like Kaggle [1]. We left out large datasets, since plotting all lines in the plot would have led to overplotting and it would have been impossible for human observers to identify angles. We also tried to avoid datasets with a majority of categorical dimensions. Dimensions consisting of only a few categories (e.g., boolean data) caused particular patterns in the plot that we wanted to avoid. The datasets we were interested in contained a manageable number of rows and columns (i.e., could be rendered without causing overlaps) and predominantly numerical values.

Table 1: The datasets we used for the statistical analysis contained a moderate number of columns and rows and only a small portion of categorical attributes.

Dataset	*Content*	*Rows*	*Columns*
Cereals	nutritional information of 80 cereal brands	80	16
Cars	information about different car brands from the year 2022	199	16
WHO	information about development factors for countries in the world for the year 2000	193	22
Health	data about human subjects that were evaluated for various health metrics	374	13

The four selected datasets were imported into our analysis application. We used a collection of normally distributed values of aspect ratios. For every aspect ratio we exported an analysis file for all datasets. The individual analysis files were later combined into one complete dataset. We aimed to find groups where the angle parameters are distributed similarly within the aspect ratios. We applied *k-means clustering* on the angle parameters to find aspect ratios with similar behavior. Since we had calculated more than one angle parameter, we extended standard k-means clustering to work with multidimensional vectors. The clustering was performed in Python using the *scikit-learn* package. We used the elbow method to estimate the number of clusters, where we calculated the total within the sum of squares for each k number of clusters and plotted the result as a line. Furthermore, the average silhouette and Calinski-Harabasz methods were applied. The optimal number of clusters was estimated to be 3 in all cases.

The cluster analysis results are shown in Figure 2. In the first plot, the cluster sizes are depicted. One particular distribution of angle parameters (*cluster2*) was found more often in the data than the other two

[1] https://kaggle.com

(*cluster0* and *cluster1*). We then plotted the distribution of clusters among different aspect ratios, shown in the plot on the right. We calculate the aspect ratio as width divided by height. Smaller aspect ratios correspond to portrait orientations, while larger ratios represent landscape orientations. When looking at the area chart, we can see that larger aspect ratios tend to have less cluster variety than smaller aspect ratios. Data points with larger aspect ratios are primarily put into one cluster (*cluster2*), which depicts a more uniform distribution of angle parameters.

3.2 User Study

In the user study, we aimed to gain more information on how easy it is for human observers to extract information about the angles from parallel coordinate plots under varying aspect ratios. We conducted a web-based user study asking participants to judge the correlation between two axes based on the line angles.

3.2.1 User Study Design

In the user study, we only used representations for two axes with lines in between. We are aware that this does not show an entire parallel coordinates plot. However, the focus of the user study was on angles in particular. Therefore, we wanted to ensure that participants focused on the angles and were not distracted by other axes, maybe confused by the axes in question with different relationships, or looked elsewhere.

Table 2: The user study parameters from which we, in total, generated 135 different images to be used in the study.

Correlation	# Lines	Aspect Ratio
-0.97 to 0.0 to 0.97	100, 200, 300	16:9, 4:3, 1:1, 3:4, 9:16

In total, 57 participants finished the study. 37 participants (65%) were between 25 and 54 years old, although we also had participants within the age group $18-24$ and $55-64$. We searched for participants who already had some experience with data visualization. 25 participants (43.8%) were occupied in a company, 15 participants (26.3%) worked in academia, 15 participants (26.3%) were students, and 2 participants selected *'Other'*. One-third of the participants (36.8%) classified themselves as advanced users of data visualization, another third (33.3%) said to have intermediate experience, and the last third (29.8%) identified themselves rather as beginners.

Participants were given a link where they could access the online user study. In the beginning, they were informed that their data would be kept secure and only stored anonymously. We assigned a token

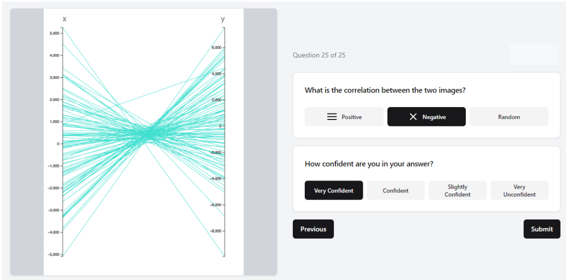

Figure 3: User study task. Participants were shown lines between two variables and had to judge the correlation based on the line angles. Participants also had to rate their confidence in their answers.

to every participant. After finishing the study, the results were imported into a database. Dropouts were not recorded. After starting the study, participants had to read an introduction to parallel coordinates, how positive or negative correlation can be judged based on the line angles (i.e., X-shape versus parallel lines), and how a random distribution can be identified. Participants then had to complete 25 tasks with randomly selected images of parallel coordinates. An example of one of the 25 tasks that participants had to solve is shown in Figure 3. Participants also had to record their confidence on a 4-point Likert scale for every task. We pre-rendered parallel coordinate axes with different sizes, aspect ratios, and correlation coefficients. The parameters we varied can be seen in Table 2. Participants reported that completing the study was easy and fast, and they did not report any issues.

3.2.2 Results

The user study results are summarized in Figure 4. Participants performed best (i.e., achieved the lowest error rate) for quadratic representations (aspect ratio 1:1). The error rate was also lower for 4:3 and 3:4 representations, as seen on the left side in Figure 4. With longer (16:9) and more narrow (9:16) settings, participants started to make more errors. The difference in the distribution of the correct and incorrect answers was statistically significant for aspect ratios 1:1 and 9:16 ($p < 0.0001$). The difference was not statistically significant for the other pairs of aspect ratios. The error rate changes according to the correlation value, as shown in Figure 4 on the right side. Generally, the error rate was lower for negatively correlated variables and higher for positively correlated variables. For negatively and positively correlated variables, the error rate was lower for strong correlations (< 0.9 and > 0.9). The confidence scores of the participants were equally distributed for all aspect ratios. Confidence, similar to error rate, more strongly depends on the correlation.

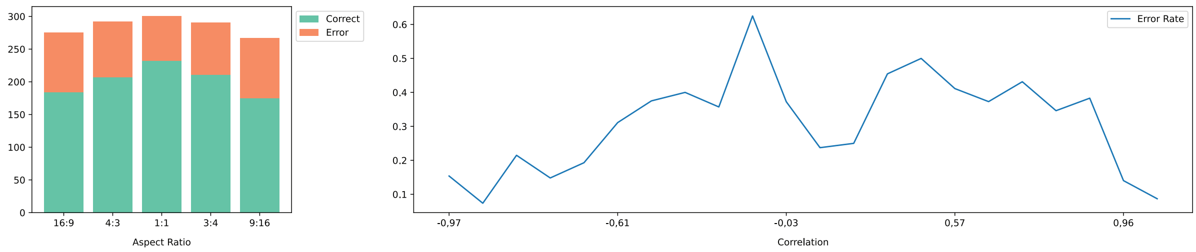

Figure 4: User study results. The ratio between correct and incorrect answers did not reveal big differences between the tested aspect ratios (left plot). However, participants performed best for quadratic, 4:3, and 3:4 settings. The error rate is also greatly influenced by the type of correlation (right plot). The error rate was generally lower for negatively correlated variables (X-shape), independent of the aspect ratio.

4 RESULTS AND INTERPRETATION

The statistical analysis revealed that angle parameters stay more consistent among larger aspect ratios. Aspect ratios were calculated as width divided by height, so larger aspect ratios refer to landscape orientation. In landscape-oriented plots, the angle parameters stay more consistent even under changing sizes, while square or portrait-oriented plots behave less predictably.

The results of the user study were less significant. The results indicate that human observers' detection of angle parameters stays relatively consistent along aspect ratios between 4:3 and 3:4. For more elongated settings (16:9 and 9:16), participants started to make more errors. The error rate is closely related to correlation. Our results confirm earlier studies (Heinrich and Weiskopf, 2015) where it was stated that negative correlation leads to a very strong visual pattern in the plot, in contrast to a less pronounced pattern of parallel lines in the case of a positive correlation.

For designers and programmers integrating parallel coordinates into dashboards, we can present first preliminary guidelines to rely on. Derived from our statistical analysis and the user study, we suggest to **rely on landscape orientation** and **quadratic to 3:4/4:3 settings for the individual variable connections**. Landscape orientations seem less prone to abrupt changes in the angle parameters when the size of the plot changes. The error rates of human observers were satisfactory for quadratic to 3:4/4:3 settings for every two axes connections. In a responsive or dynamically resizable parallel coordinate view, it might be preferable only to allow landscape orientations, if possible.

Our results depict a first step towards a better understanding of properly integrating plots into dashboard environments. Our study links to previous research results on the *banking to 45°* rule for line charts and studies on the effect of aspect ratio on bar charts and scatterplots (as outlined in Section 2). We strongly believe that further research is needed to fully understand the effect of aspect ratios on parallel coordinates and to make solid statements about the optimal aspect ratio for a given plot. First of all, we conducted both studies using relatively small datasets. While this was sufficient to gain first results, we would like to conduct further studies with larger and more dense datasets. Also, the effect of categorical values on angle parameters needs to be understood better. Second, we did not study the effects of line width, color, and other design decisions on the perception of angles by human observers. Studies on the perception of patterns in scatterplots under varying dot size and opacity exist (Strain et al., 2024), and we would like to extend this knowledge by studying similar effects for parallel coordinates.

5 CONCLUSION

We presented preliminary results of a statistical analysis of angle parameters and a user study of the perception of angles in parallel coordinate plots under varying aspect ratios. From the statistical analysis, we can derive that landscape-oriented plots tend to have more consistent angle parameters even when changing the plot size. From the user study we can derive that human observers prefer almost quadratic settings for the individual variable connections. Based on these first results, we can suggest that dashboard designers take care that parallel coordinate plots are presented in landscape orientation.

We were generally surprised about the lack of perception studies on parallel coordinates. Previous studies compared the effectiveness of finding correlations between scatter plots and parallel coordinates (Li et al., 2010), studied the learning effect of novice users (Siirtola et al., 2009), and identified barriers for reading parallel coordinates (Srinivas et al., 2024). However, profound perception studies of the depiction of patterns in parallel coordinates under different circumstances are still missing. In the future, we will continue our research on finding guidelines for integrating parallel coordinates into multi-view and desktop environments.

ACKNOWLEDGEMENTS

VRVis is funded by BMK, BMAW, Styria, SFG, Tyrol and Vienna Business Agency in the scope of COMET which is managed by FFG (No. 879730). The work was funded by the project REINFORCE (FFG, No. 4141421).

REFERENCES

Antolini, F., Terraglia, I., and Cesarini, S. (2024). Integrating multiple data sources to measure sustainable tourism in Italian regions. *Socio-Economic Planning Sciences*, 95:101959.

Bach, B., Freeman, E., Abdul-Rahman, A., Turkay, C., Khan, S., Fan, Y., and Chen, M. (2023). Dashboard Design Patterns. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):342–352.

Ceja, C. R., McColeman, C. M., Xiong, C., and Franconeri, S. L. (2021). Truth or Square: Aspect Ratio Biases Recall of Position Encodings. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):1054–1062.

Chen, X., Zeng, W., Lin, Y., AI-maneea, H. M., Roberts, J., and Chang, R. (2021). Composition and Configuration Patterns in Multiple-View Visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):1514–1524.

Cibulski, L., May, T., Schmidt, J., and Kohlhammer, J. (2023). COMPO*SED: Composite Parallel Coordinates for Co-Dependent Multi-Attribute Choices. *IEEE Transactions on Visualization and Computer Graphics*, 29(10):4047–4061.

Cleveland, W. S. (1986). The Elements of Graphing Data. *The American Journal of Psychology*, 99(3):443–448.

Conrow, L., Fu, C., Huang, H., Andrienko, N., Andrienko, G., and Weibel, R. (2023). A conceptual framework for developing dashboards for big mobility data. *Cartography and Geographic Information Science*, 50(5):495–514.

Dasgupta, A. and Kosara, R. (2010). Pargnostics: Screen-Space Metrics for Parallel Coordinates. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):1017–1026.

Deng, D., Wu, A., Qu, H., and Wu, Y. (2023). DashBot: Insight-Driven Dashboard Generation Based on Deep Reinforcement Learning. *IEEE Transactions on Visualization and Computer Graphics*, 29(01):690–700.

Epperson, W., Wongsuphasawat, K., Whilden, A., Du, F., and Talbot, J. (2023). A Declarative Specification for Authoring Metrics Dashboards. In *Proceedings of the IEEE Workshop Visualization in Data Science*, VDS '23, pages 6–10, Melbourne, Australia.

Fink, M., Haunert, J.-H., Spoerhase, J., and Wolff, A. (2013). Selecting the Aspect Ratio of a Scatter Plot Based on Its Delaunay Triangulation. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2326–2335.

Firat, E. E., Denisova, A., Wilson, M. L., and Laramee, R. S. (2022). P-Lite: A study of parallel coordinate plot literacy. *Visual Informatics*, 6(3):81–99.

Firat, E. E., Swallow, B., and Laramee, R. S. (2023). PCP-Ed: Parallel coordinate plots for ensemble data. *Visual Informatics*, 7(1):56–65.

Goudsmit, J., Otter, R. T. A., Stoter, I., van Holland, B., van der Zwaard, S., de Jong, J., and Vos, S. (2022). Co-Operative Design of a Coach Dashboard for Training Monitoring and Feedback. *Sensors (Basel)*, 22(23):9073.

Hauser, H., Ledermann, F., and Doleisch, H. (2002). Angular brushing of extended parallel coordinates. In *Proceedings of the IEEE Symposium on Information Visualization*, INFOVIS '02, pages 127–130, Boston, MA, USA.

Heer, J. and Agrawala, M. (2006). Multi-Scale Banking to 45 Degrees. *IEEE Transactions on Visualization and Computer Graphics*, 12(5):701–708.

Heinrich, J. and Weiskopf, D. (2013). State of the Art of Parallel Coordinates. In *Proceedings of 34th Annual Conference of the European Association for Computer Graphics - State of the Art Reports*, EUROGRAPHICS '13, Girona, Spain.

Heinrich, J. and Weiskopf, D. (2015). Parallel Coordinates for Multidimensional Data Visualization: Basic Concepts. *Computing in Science & Engineering*, 17(3):70–76.

Howe, C. Q. and Purves, D. (2005). Natural-scene geometry predicts the perception of angles and line orientation. *Proceedings of the National Academy of Sciences of the United States of America*, 102(4):1228–1233.

Johansson, J. and Forsell, C. (2016). Evaluation of Parallel Coordinates: Overview, Categorization and Guidelines for Future Research. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):579–588.

Johansson, J., Forsell, C., Lind, M., and Cooper, M. (2008). Perceiving Patterns in Parallel Coordinates: Determining Thresholds for Identification of Relationships. *Information Visualization*, 7(2):152–162.

Kaur, G. and Karki, B. B. (2018). Bifocal Parallel Coordinates Plot for Multivariate Data Visualization. In *Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, IVAPP '18, Funchal, Portugal.

Kelleher, C. and Wagener, T. (1985). The plane with parallel coordinates. *The Visual Computer*, 1:69–91.

Kelleher, C. and Wagener, T. (2011). Ten guidelines for effective data visualization in scientific publications. *Environmental Modelling & Software*, 26(6):822–827.

Kristiansen, Y. S., Garrison, L., and Bruckner, S. (2022). Semantic Snapping for Guided Multi-View Visualization Design. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):43–53.

Li, J., Martens, J.-B., and van Wijk, J. J. (2010). Judging Correlation from Scatterplots and Parallel Coordinate Plots. *Information Visualization*, 9(1):13–30.

Lin, Y., Li, H., Wu, A., Wang, Y., and Qu, H. (2024). DMiner: Dashboard Design Mining and Recommendation. *IEEE Transactions on Visualization and Computer Graphics*, 30(7):4108–4121.

Lughbi, H., Mars, M., and Almotairi, K. (2024). A Novel NLP-Driven Dashboard for Interactive CyberAttacks Tweet Classification and Visualization. *Information*, 15(3):137.

Ma, R., Mei, H., Guan, H., Huang, W., Zhang, F., Xin, C., Dai, W., Wen, X., and Chen, W. (2021). LADV: Deep Learning Assisted Authoring of Dashboard Visualizations From Images and Sketches. *IEEE Transactions on Visualization and Computer Graphics*, 27(9):3717–3732.

Matheus, R., Janssen, M., and Maheshwari, D. (2020). Data science empowering the public: Data-driven dashboards for transparent and accountable decision-making in smart cities. *Government Information Quarterly*, 37(3):101284.

McNutt, A., Kindlmann, G., and Correll, M. (2020). Surfacing Visualization Mirages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '20, page 1–16, Honolulu, HI, USA.

Midway, S. R. (2020). Principles of Effective Data Visualization. *Patterns*, 1(9):100141.

Pandey, A., Srinivasan, A., and Setlur, V. (2023). MEDLEY: Intent-based Recommendations to Support Dashboard Composition. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):1135–1145.

Qu, Z. and Hullman, J. (2018). Keeping Multiple Views Consistent: Constraints, Validations, and Exceptions in Visualization Authoring. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):468–477.

Rickman, J. M. (2018). Data analytics and parallel-coordinate materials property charts. *npj Computational Materials*, 4:5.

Sahann, R., Gajic, I., Möller, T., and Schmidt, J. (2021). Selective Angular Brushing of Parallel Coordinate Plots. In *Proceedings of EuroVis Short Papers*, EuroVis '21, Zurich, Switzerland.

Sarikaya, A., Correll, M., Bartram, L., Tory, M., and Fisher, D. (2019). What Do We Talk About When We Talk About Dashboards? *IEEE Transactions on Visualization and Computer Graphics*, 25(1):682–692.

Setlur, V., Correll, M., Satyanarayan, A., and Tory, M. (2024). Heuristics for Supporting Cooperative Dashboard Design. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):370–380.

Siirtola, H., Laivo, T., Heimonen, T., and Räihä, K.-J. (2009). Visual Perception of Parallel Coordinate Visualizations. In *Proceedings of the 13th International Conference Information Visualisation*, IV '09, pages 3–9, Barcelona, Spain.

Soni, P., de Runz, C., Bouali, F., and Venturini, G. (2024). A survey on automatic dashboard recommendation systems. *Visual Informatics*, 8(1):67–79.

Srinivas, C., Firat, E. E., Laramee, R. S., and Joshi, A. (2024). An Inductive Approach for Identification of Barriers to PCP Literacy. In *IEEE VIS Workshop on Visualization Education, Literacy, and Activities*, EduVIS '24, St. Pete Beach, FL, USA.

Strain, G., Stewart, A. J., Warren, P. A., and Jay, C. (2024). Effects of Point Size and Opacity Adjustments in Scatterplots. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '24, Honolulu, HI, USA.

Talbot, J., Gerth, J., and Hanrahan, P. (2011). Arc Length-Based Aspect Ratio Selection. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2276–2282.

Talbot, J., Gerth, J., and Hanrahan, P. (2012). An Empirical Model of Slope Ratio Comparisons. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2613–2620.

Wang, Y., Wang, Z., Fu, C.-W., Schmauder, H., Deussen, O., and Weiskopf, D. (2019). Image-Based Aspect Ratio Selection. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):840–849.

Wang, Y., Wang, Z., Zhu, L., Zhang, J., Fu, C.-W., Cheng, Z., Tu, C., and Chen, B. (2018). Is there a robust technique for selecting aspect ratios in line charts? *IEEE Transactions on Visualization and Computer Graphics*, 24(12):3096–3110.

Ware, C. (2012). *Information Visualization: Perception for Design*. Morgan Kaufmann Publishers Inc.

Wei, Y., Mei, H., Zhao, Y., Zhou, S., Lin, B., Jiang, H., and Chen, W. (2020). Evaluating Perceptual Bias During Geometric Scaling of Scatterplots. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):321–331.

Wexler, S., Shaffer, J., and Cotgreave, A. (2017). *The Big Book of Dashboards: Visualizing Your Data Using Real-World Business Scenarios*. John Wiley & Sons, Inc.

Wu, A., Wang, Y., Zhou, M., He, X., Zhang, H., Qu, H., and Zhang, D. (2022). MultiVision: Designing Analytical Dashboards with Deep Learning Based Recommendation. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):162–172.

Zeng, W., Chen, X., Hou, Y., Shao, L., Chu, Z., and Chang, R. (2024). Semi-Automatic Layout Adaptation for Responsive Multiple-View Visualization Design. *IEEE Transactions on Visualization and Computer Graphics*, 30(7):3798–3812.

Zhang, Y., Sun, Y., Gaggiano, J. D., Kumar, N., Andris, C., and Parker, A. G. (2023). Visualization Design Practices in a Crisis: Behind the Scenes with COVID-19 Dashboard Creators. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):1037–1047.

Zhuang, M., Concannon, D., and Manley, E. (2022). A Framework for Evaluating Dashboards in Healthcare. *IEEE Transactions on Visualization and Computer Graphics*, 28(4):1715–1731.