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The Effects of Visual and Design Features on the Perception of Correlation in Scatterplots

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Contents

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Declaration of originality

I hereby confirm that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright statement

Acknowledgements

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Chapter 1

Introduction

1.1 Research Motivation

1.2 Contributions

1.3 Included Publications

The research described in chapters 4, 5, 6, and 7 in this thesis is adapted from earlier publications, the last of which under review as of writing. To avoid repetition, information and discussion that would be repeated has been consolidated into the literature review and general methodology chapters. *Gabriel Strain* is the primary author of all included papers.

- *The Effects of Contrast on Correlation Perception in Scatterplots* [33] is reproduced in Chapter 4. Sections 4.5.2, 4.6.2, 4.5.3, 4.6.3, 4.5.4, 4.6.4, and4.7 contain minimally altered parts of the published article.
- *Adjusting Point Size to Facilitate More Accurate Correlation Perception in Scatterplots* [32] is reproduced in Chapter 5. Sections 5.4.2, 5.4.3, 5.4.4, and 5.5 contain minimally altered parts of the published article.
- *Effects of Point Size and Opacity Adjustments in Scatterplots* [34] is reproduced in Chapter 6. Sections 6.4.2, 6.4.3, 6.4.4, and 6.5 contain minimally altered parts of the published article.
- *Effects of Alternative Scatterplot Designs on Belief* (*under review*) is reproduced in Chapter 7. Sections 7.4, 7.5.2, 7.5.3, 7.5.4, and 7.6 contain minimally altered parts of the published article.

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Chapter 3

General Methodology

3.1 Introduction

In this chapter we describe our research methodologies. Chapters 4, 5, and 6 share most aspects of experimental method, while the experiment described in chapter 7 differs substantially. Throughout this chapter, the reader should assume that we are referring to the entire body of experimental work this thesis describes. Methods that differ regarding the final experiment in chapter 7 are detailed along the way. In this chapter, we discuss our experimental designs, the tools we use to build and run our experiments, our approach to statistical analyses, and the computational methods and practices we employed particularly with regards to reproducibility and open science.

3.2 Experimental Methods

It is important to acknowledge that the way in which we conduct experiments influences what we find and the conclusions that we may draw from those findings. The decisions that lead us to designing experiments in certain ways must be based not only on theory, but also on the practical constraints imposed by external factors on the research team. Concerns such as time, convenience, and cost must be addressed, and a compromise between research that is *valuable* and research that is *doable* must be reached. We focused on pragmatism and impact throughout the course of this research project; happily, the research journey we embarked on resulted in methodologies that satisfied both principles. It is for this reason that we consider the framework we present to be a key contribution of this thesis.

3.2.1 Experimental Design

All but our final experiment utilised within-participants designs. Each participant saw all experimental stimuli and provided a judgement of correlation using a sliding scale between 0 and 1 (see Figure 3.1). Experiments 1 to 3 featured featured a single experimental factor of design, all with 4 levels corresponding to scatterplots with different design features. Experiment 4 employed a factorial 2×2 design. Experiment 5 is a departure from the shared experimental paradigm of the previous experiments, and features a 1 factor, 2 level between-participants design.

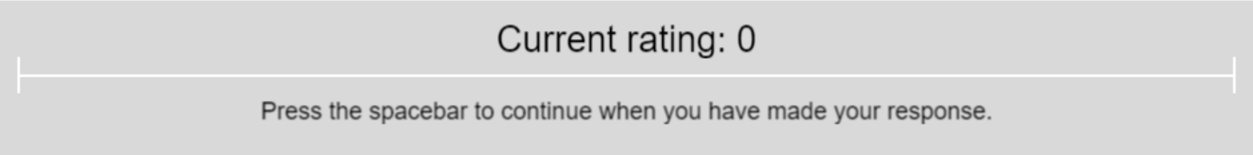
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Figure 3.1. An example of the slider participants used to estimate correlation in experiments 1-4.

3.2.2 Tools for Testing

Whatever the design of our experiments, software plays a crucial role in allowing us to carry them out. Fortunately, at the time of writing, there is a wealth of tools available to facilitate the testing of visualisations both in traditional lab-based tests and in online experiments. As we adhere to the principles of open and reproducible research [4], we discount closed-source software, such as Gorilla [2] or E-prime [14], as these rely on paid licenses and do not allow us to share code with future researchers. We settled on using PsychoPy [25] due to its open-source status, flexibility regarding graphical and code-based experimental design, and high level of timings accuracy [8]. Using such a open-source tool not only facilitated our own learning with regard to experiment building, but also enables to contribute further examples of visualisation studies by hosting the resulting experiments online for use and modification by future researchers.

We elected to pursue online testing throughout this thesis. Doing so is much quicker than carrying out in-person lab-based testing, meaning we can collect data from a much larger number of participants. This reduces the chances of detecting false positives during analysis and ensures adequate levels of power despite the potential for small effects sizes. Online testing also affords us access to diverse groups of participants across our populations of interest, especially when compared to the relatively homogeneous student populations usually accessed by doctoral researchers. Research has identified online experimentation as producing reliable results that closely match those found in traditional lab-based experiments [3, 15, 28], especially with large sample sizes. Due to its integration with PsychoPy, we chose to use Pavlovia (pavlovia.org) to host all the experiments described in this thesis. Section 3.5.3 contains links to all experiments publicly hosted on Pavlovia's GitLab instance.

3.2.3 Recruitment & Participants

Recruitment of participants online is possible through a range of service providers, each with advantages and disadvantages. Research evaluating a number of these providers recently found that Prolific [29] and CloudResearch provide the highest quality data for the lowest cost [13]; we elected to use the former due to familiarity with the system. Despite these findings, there has also been evidence of low data quality and skewed demographics affecting even high quality platforms tailored towards academic research. On the 24th of July, 2021, the Prolific.co platform went viral on social media [10], leading to a participant pool heavily skewed towards young people identifying as female. At the time, Prolific did not manually balance the participants recruited for a study. We addressed this in our pilot study (see Section 4.2) by preventing participants who joined after this data from participating, in addition to manually requesting a 1:1 ratio of male to female participants. The demographic issues settled quickly, however we maintained our screened 1:1 ratio for the remainder of the experiments.

The first experiment we conducted was a pilot study (see Section 4.2 for full details) investigating a very early iteration of the point opacity manipulation in combination with exploratory work around plot size and correlation estimation. At the time, the author was relatively naive to the intricacies of recruiting research participants online, and thus experienced issues with regards to participant engagement. Each experiment, including the pilot, included attention check questions in which participants were instructed to ignore the stimulus and provide a specific answer. We stated in the advert for each experiment that failure of more than 2 attention check items would result in a submission being rejected. This pilot study suffered from a rejection rate of 57.5%, indicating that we were experiencing low levels of participant engagement. For our following studies, we therefore followed published guidelines [24] to address these issues; specifically, we required that participants:

- Had previously completed at least 100 studies on Prolific.
- Had an acceptance rate of at least 99% for those studies. [1]

Following implementation of these pre-screen criteria, the rejection rate for our next experiment fell to ~5%. Rejection rates were similar for the remainder of our experiments. Exact numbers of accepted and rejected participants can be found in the **Participants** sections of each experiment.

3.2.4 Creating Stimuli

All our stimuli were created using `ggplot2` in R. Specific versions are cited separately with regard to the specific visualisations produced for each experiment. We followed identical principles regarding data visualisation design for each experiment bar the last, which is discussed *in situ*.

We designed with the intention of isolating and addressing a perceptual effect; the underestimation of correlation in positively correlated scatterplots. For this reason, we sought to remove the potential for other design factors to have effects on correlation estimation. To this end, we removed most of the conventionally present visual features of scatterplots, including axis labels, tick labels, grid lines, and titles. We elected to preserve the axis ticks themselves. Figure 3.2 demonstrates the basic design of the scatterplots used in experiments 1 to 4.

3.3 Analytical Methods

3.3.1 Linear Mixed-Effects Models

To investigate whether the experimental manipulations we test have actual effects on the interpretations participants provide, we must employ appropriate statistical testing. This involves taking into account the variability in responses that can be attributed to an experimental experimental against the backdrop of other variability inherent in the dataset. To accomplish this, we utilise linear mixed-effects modelling, a broadly applicable and reliable approach that is also resistant to a variety of distributional assumption violations [31].

[1] this is a more strict rate than the 95% recommended by Peer et al. [24].

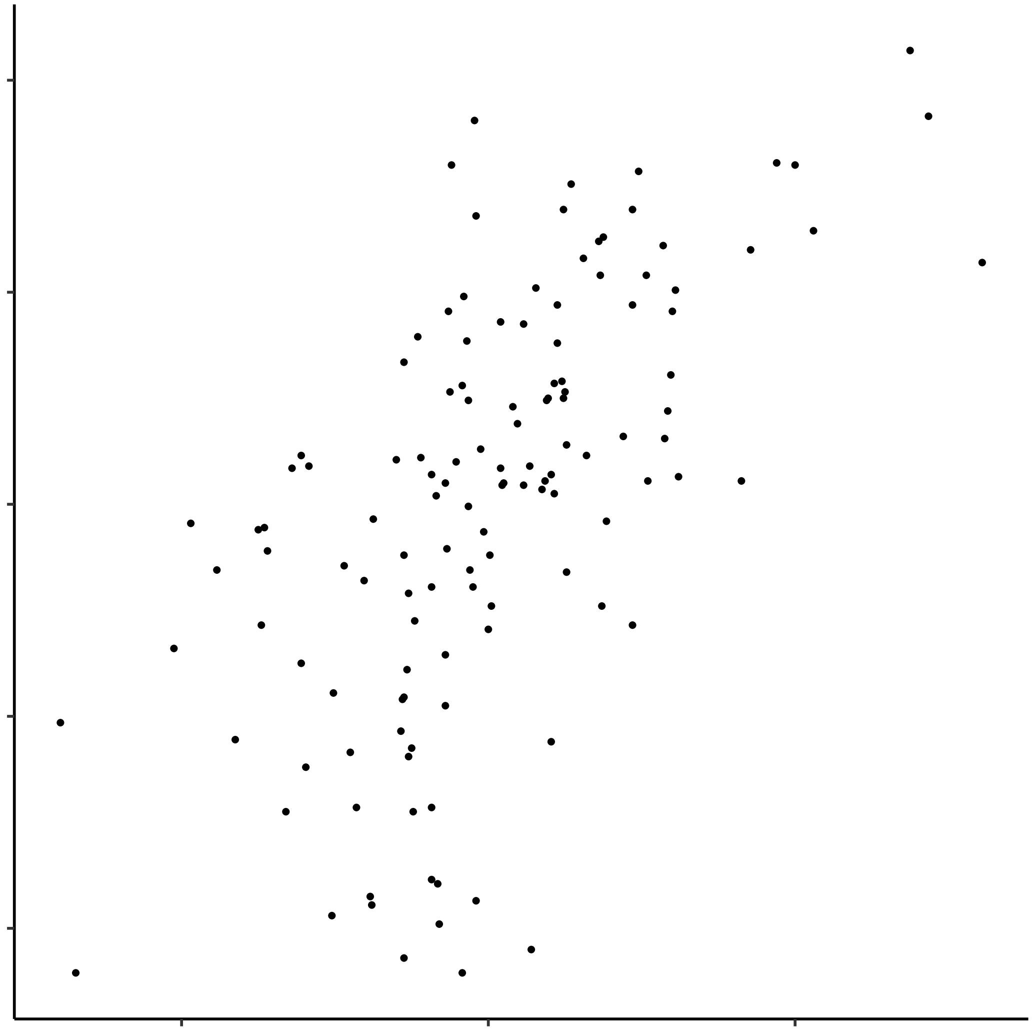

Figure 3.2. The basic design of scatterplots in experiments 1 to 4.

In a mixed-effects modelling paradigm, a distinction is made between variability that is thought to arise as a result of an experimental manipulation (fixed effects), and that which arises due to differences between, for example, participants or particular experimental items (random effects). When a variable is manipulated by a researcher in an experiment, each level of that variable is present, meaning it is appropriate to be modelled as a fixed effect. When only a *subset* of levels of a variable is present, such as a sample of all possible participants or experimental items, then this variable is appropriate for modelling as a random effect. Typically, mixed-effects models require the specification of *intercepts*; these are different baselines for each participant or item that reflect random deviations from the mean of the dependent variable. Mixed-effects models may also specify random *slopes*; these are differences in the magnitude of the difference between levels of the independent variable for each participant or experimental item [9]. Figure 3.3 visualises these concepts.

Throughout the course of this thesis we attempt to model both random intercepts and slopes in order to capture the maximum amount of variability present in our datasets.

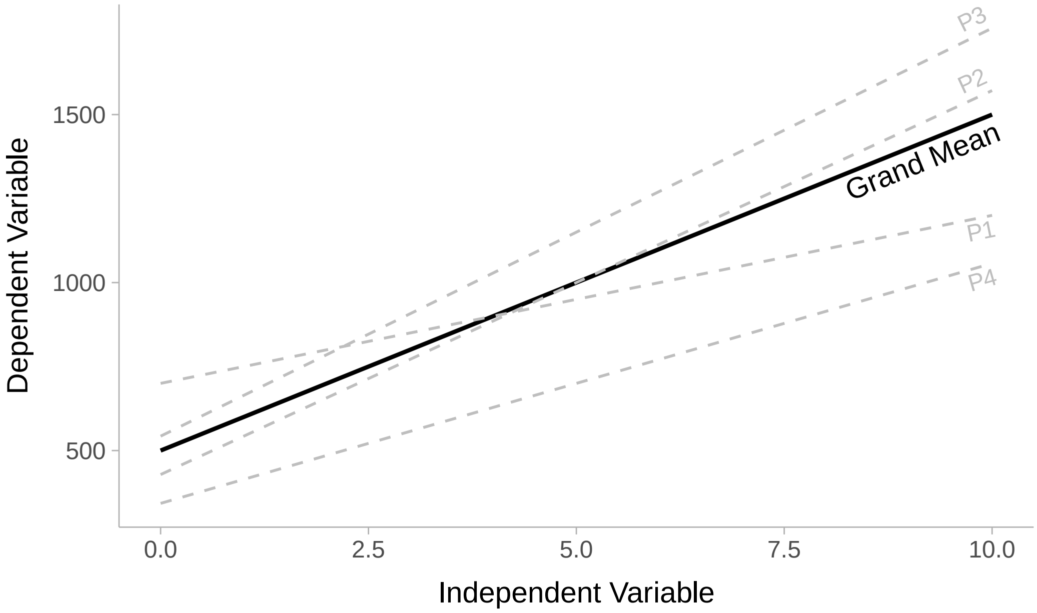

Figure 3.3. Visualising random intercepts and slopes for a theoretical experiment with 4 participants. The grand mean of the dependent variable is shown as a solid line, while each separate random intercept is drawn with dashed lines. Each line has a different gradient, representing different random slopes for each participant. This graphic was inspired by those featured in Brown, 2021 [9].

3.3.2 Advantages Over Aggregate-Level Statistical Tests

Traditional analysis of the data that we collect throughout this thesis would involve the use of repeated measures analyses of variance (ANOVAs). This technique assesses whether there are significant differences in means of dependent variables between conditions. While these techniques are commonplace, they do not allow for comparisons of differences across the full range of participant responses, nor do they allow for simultaneous consideration of by-item and by-participant variance. It is for these reasons that we employ linear mixed-effects models throughout this thesis; doing so simply allows us to appreciate the data story in a broader and more detailed fashion.

3.3.3 Ordinal Modelling

In experiment 5, participants used Likert scales to provide responses. These scales capture whether one rating is higher or lower than another, however they do not quantify the magnitude of the difference between levels of rating. Metric modelling, such as linear regression, treats the response options to a Likert scale as if they were numeric. Doing so assumes equal levels of difference between ratings, when in reality there is no theoretical reason to assume so. Metric modelling is therefore considered inappropriate for modelling responses to Likert scales [19]. In light of these issues, we use `ordinal` package [11] in R to build cumulative link mixed effects models for the analysis of Likert scale data. This allows us to treat our Likert responses as an ordered factor as opposed to a continuous response scale.

3.3.4 Model Construction

Choices are inherent in every type of statistical analysis, and can play a large role in the conclusions that are drawn from them. In linear mixed-effects modelling, deciding what is a fixed and what is a random effect is straightforward; deciding how to specify random effects is a more complicated matter. Barr et al. [5] argue that for fully repeated measures designs, we should prefer a maximal model; one with random intercepts and slopes for each participant and experimental item. More recently, Bates et al. [6] have argued that attempting to specify maximal models for insufficiently rich datasets may lead to overfitting and unreliable conclusions. In light of this we sought a more systematic approach to selecting the random effects structure of a given model.

In an attempt to balance simplicity, explanatory power, and model convergence (whether or not a solution can be found), we chose to use the `buildmer` package [35] in R to automate the selection of our model specifications. Having been provided with a maximal model, `buildmer` uses stepwise regression to select the most complex model structure that successfully converges. Following this, random effects terms that fail to explain a significant amount of variance in the dataset are dropped. This results in a model that captures the maximal amount of feasible variability while minimising redundancy. Note that we do not rely on `buildmer` as a modelling *panacea*; models are still based on theoretical underpinnings and are evaluated critically.

3.3.5 Effects Sizes

Our approach to effects sizes evolved throughout the course of the research project due to reviewer feedback and an increasing appreciation of complexities of effect sizes when discussing linear mixed-effects models. Experiments 1, 2, and 3 used the `EMAtools` package [18] to calculate equivalent Cohen's *d* effect sizes. Experiment 4 did not feature a theoretically sound baseline condition, meaning Cohen's *d* was inappropriate. We therefore used the `r2glmm` package [17] to calculate semi-partial R^2. We use this in lieu of a traditional measure of effect size to demonstrate the unique variance in our dependent variable explained by each level of our independent [23]. Experiment 5 features a much simpler modelling situation, and returns to providing equivalent Cohen's *d* values, this time calculated by converting odds ratios using the `effectsize` package [**effectsize**]. More details on specific calculations, measures, and conclusions can be found *in situ*.

3.3.6 Reporting Analyses

Throughout this thesis, we take a broad approach to the reporting of statistical analyses; while we consider our analytical methods and conclusions to be sound, we also present a range of statistics to allow the reader to draw their own conclusions should they wish. Statistics are visualised where appropriate, and where visualisation aids understanding and interpretation. In addition, we include details about model structures and the issues we tackled when modelling, for transparency [22].

3.4 Computational Methods

We took an approach to computational methods that sought to marry convenience, simplicity, and reproducibility. Often, this meant that what would otherwise be a makeshift script followed by copy-pasting of results into overleaf ended up being an involved exercise in functional programming and code wrangling. This involved effort and time, particularly in the early stages of the project, however has yielded a number of benefits. Many of the techniques developed early in the project proved to be instrumental later on, meaning time was, on the whole saved. Additionally, we share these techniques, principles, and practices to enable future researchers to learn, where we had to struggle. In this section, we detail our approaches to computational methods, including how we utilised the idea of **executable papers**, and how we used containerised environments to capture a *freeze-frame* of our analyses.

3.4.1 Executable Reporting

Each paper published throughout this project, each chapter in this thesis, and the thesis itself, has been written to be executable. Doing so allows us to package our research such that a lay person can follow simple instructions to recreate our work, while also facilitating literate programming, or the close alignment of documentation and underlying code [27].

The use of a literate programming paradigm to generate reports (usually using LaTeX) has a rich history. Here, we focus on that history specifically with regards to the language used throughout the course of this project, R. `Sweave` [**leisch_2002**], written in 2002, allowed R code to be integrated into LaTeX documents. This was followed by Yihui Xie's `knitr` [36], which expanded `Sweave` functionality and improved integration with tools such as `pandoc` [20]. `knitr` uses `Rmarkdown` [37] to mix markdown-flavoured text with code chunks into a document that can easily be rendered into an appropriately-formatted conference or journal pdf; this workflow was used for the paper associated with experiments 1 and 2. `Quarto` [1], released in 2022, further expands on `Rmarkdown` functionality, and removes reliance on R or Rstudio. We used `Quarto` for the remainder of the papers associated with this project, and for the present thesis.

Writing executable or dynamic documents allows results to be re-generated whenever the document is rendered. This includes any associated data visualisations and statistical modelling. Structuring documents like this effectively "open up" research by allowing others to view the code that performed the analysis and generated the data visualisations, in addition to guarding against accusations of questionable research practices through high levels of transparency [16]. This paradigm also allows for the caching of computationally expensive statistical models.

3.4.2 Containerised Environments

Providing the code associated with a project, even when that code is integrated into a literately programmed executable paper, is necessary, but not sufficient, for enabling adequate reproducibility. Previous work has found many instances where publicly-accessible code could not reproduce the results included in the corresponding document or failed to run [**trisovic_2022**, 12, 30]. Poor programming practices accounted for a significant portion of these issues, highlighting the issue of researchers without technical backgrounds being expected to produce high quality technical documentation. Elsewhere, differences in computational environment, package versions, and operating systems have been identified as responsible for the non-replication of results. Large research projects, such as this, can include hundreds of functions from scores of packages, meaning that small changes can critically break code.

To address these issues, we elected to use containers, specifically, those created by `Docker` [7, 21]. 1979 saw the development of `chroot`, which is able to isolate an application's file access. The following 50 years has seen rapid development and uptake of containerisation software, mostly within the software security and development communities. Docker, released in 2014, is a popular, lightweight containerisation tool that enables a precise recreation of computational environments. By recording software versions and dependencies, we avoid the potential for broken code in the future, and by publicly hosting papers as GitHub repositories that build into Docker containers, we ensure that future researchers can interact with our code and data in the same computational environment we did when carrying out the research.

3.5 Reproducibility In This Thesis

gold standard of reproducibility [26]

3.5.1 Sharing Data and Code

3.5.2 Executable Papers and Docker Containers

3.5.3 Experimental Resources

Everything needed to run each experiment is included in the corresponding GitLab repository. Links to these repositories are also provided in the sections concerning each experiment.

Chapter 4

Experiment 1: https://gitlab.pavlovia.org/Strain/exp_uniform_adjustments

Experiment 2: https://gitlab.pavlovia.org/Strain/exp_spatially_dependent

Chapter 5

Experiment 3: https://gitlab.pavlovia.org/Strain/exp_size_only

Chapter 6

Experiment 4: https://gitlab.pavlovia.org/Strain/size_and_opacity_additive_exp

Chapter 7

Experiment 5 Pre-Study: https://gitlab.pavlovia.org/Strain/beliefs_scatterplots_pretest

Experiment 5 Main Study (Group A): https://gitlab.pavlovia.org/Strain/atypical_scatterplots_main_a

Experiment 5 Main Study (Group B): https://gitlab.pavlovia.org/Strain/atypical_scatterplots_main_t

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Appendices

Appendix A

First appendix

A.1 Section in Appendix