

University of Brighton

PGCert Learning & Teaching in Higher Education 2018/19



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INTRODUCTION

- Social Science departments are increasingly considering teaching R/RStudio instead of IBM SPSS Statistics for data analysis on research methods/statistics modules.
- Concerns exist over the steep learning curve of R/RStudio's command line interface (Figure 1) compared to the relative ease of SPSS's 'point and click' graphical user interface (Figure 2).
- Initial classroom-based evaluative studies suggest students will overcome this barrier if motivated (e.g. Poldrack, 2018) but there is no empirical support.
- Motivation is argued to be the most important predictor of achievement in higher education (Biggs & Tang, 2011) and amongst non-specialist (i.e. non computing/maths) introductory statistics students (e.g. Field, 2010; 2014).
- Research is yet to identify which factors might motivate these learners to persist with R/RStudio. The present project addressed this gap.

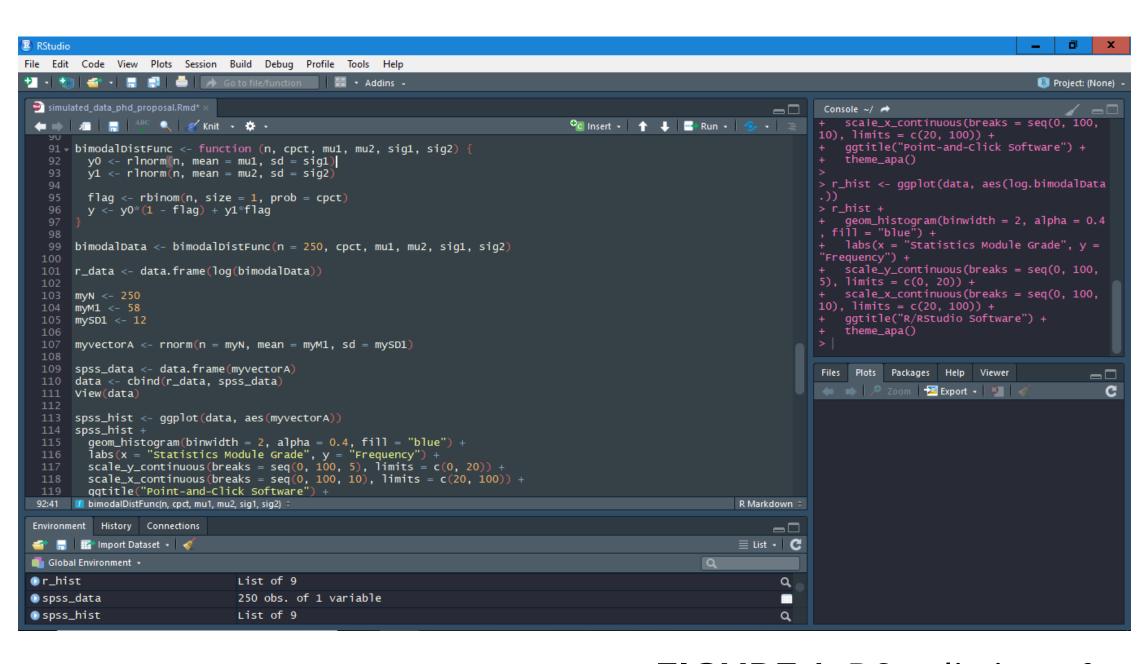


FIGURE 1: RStudio interface

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FIGURE 2: SPSS interface

Motivating social science faculty &

students to overcome barriers to learning

R Studio statistics software



"I think I'd probably still have [continued trying], because, I'd think, what... was I doing wrong? Eventually, I'll figure this out."

- Consistent with Biggs & Tang (2011), motivation was enhanced by deeply held beliefs that learning R/RStudio was possible with practice and support (i.e. high selfefficacy).
- Faculty perceived efficacy to be considerably lower in students (contributing to anxiety), suggesting it may require cultivation.
- Normalising errors and uncertainty when learning enhanced efficacy and faculty were comforted by the realisation they were not expected to learn by rote.



Value

"I needed to do robust analyses and you can't do [those] analyses in SPSS."

"I didn't want our university... to get left behind."

- Consistent with Biggs & Tang (2011), ppts were motivated to learn R/RStudio for workrelated benefits (i.e. it had perceived value).
- Embedding concrete examples of specific research tasks helped faculty notice the usefulness of R/RStudio to their work.
- Faculty also noted students rarely see the value of research/statistics (but see e.g. Field, 2014) and expected this to be especially true for R/RStudio.

Anxiety

"I needn't have been so nervous, I was able to take it at my own pace without worrying what everyone else was doing."

- Extending Biggs & Tang (2011), faculty identified that anxiety surrounding statistics (including software) can reduce motivation.
- Elsewhere (see e.g. Field, 2010; 2014), anxiety has been identified as a barrier to learning statistics but the mechanisms are debated.
- Faculty's own anxieties were relieved by empathetic instructor support and self-paced learning that avoided peer comparison.



RECOMMENDATIONS FOR PRACTICE

LIMITATIONS & FUTURE RESEARCH

Formative flipped learning tasks (Bergmann and Sams, 2012) throughout modules may help to:

Participants: Teaching staff that had recently

completed introductory R/RStudio training.

 $2 \times n = 3 60-90 \text{ minute semi-structured group}$

interviews explored both learning and teaching

Analysis: Inductive; Thematic (Braun et al., 2019).

RESULTS & DISCUSSION (key themes in centre panel)

The present study was based on experiences of staff

learners whose motivation processes may differ to

research should explore student motivation directly.

student learners (low external validity). Future

- Make students regularly accountable for learning
- Encourage ongoing self-paced leaning outside of the classroom to reduce anxiety
- Provide students with tangible, evolving evidence of their learning progression, increasing efficacy
- Apply a project-based learning approach (Hmelo-Silver, 2004) that highlights real-world relevance of R/RStudio in disciplines/industry/social contexts, enhancing value.
- Emphasise (ideally, model) the normalcy of mistakes in coding and avoid assessments that require rote learning of code (e.g. closed book exams) to reduce anxiety & increase efficacy.

CONCLUSIONS

METHOD

experiences.

- Educators' concerns about R/RStudio's steep learning curve are not unfounded but challenges may be mitigated by addressing the identified motivating factors within pedagogic practice.
- The present findings suggest Biggs & Tang's (2011) model does not account for all predictors of student motivation in the context of R/RStudio suggesting more challenging subjects may require additional motivators.

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Accountability

"I needed to know somebody expected me to do

something by a certain time because there was

just so many other things going on."

accountable to, allowing other tasks to take

Faculty perceived students to be outcome-

focussed, reserving learning efforts for

knowledge and skills over time.

assessments, which would be problematic

because R/RStudio requires gradual building of

motivation waned when there was no-one to be

Extending Biggs & Tang (2011), faculty

priority.