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How Automated Workflow Affect Long-Term Decrease in Cognitive Skill

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Abstract - Automated assistive tools, including generative image systems, smart layout features and AI copilots, now take over a large share of routine design work. Research on learning and memory suggests that part of the effort these tools remove is the same effort through which lasting skill is formed [3], [4]. This paper sets out a study of whether sustained reliance on such tools is linked to weaker unaided ability among design students and early-career professionals. A mixed-methods, cross-sectional design is proposed: an online questionnaire of 100 to 150 respondents from UI/UX, product and communication design, followed by six to eight interviews. The paper reviews evidence from cognitive load theory, desirable difficulties, cognitive offloading and automation research, and introduces the Friction-Retention Model, which links automated assistance to unaided skill retention through the loss of productive effort, moderated by experience, discipline and the timing of tool adoption. An analysis plan is given for each research question. The paper argues that foundational skills should be built before automation is introduced, and that assistive tools should be used in ways that keep the designer actively involved.

Keywords - Automation; Generative AI; Cognitive Offloading; Skill Retention; Desirable Difficulties; Design Education.

I. INTRODUCTION

Digital tech and AI have changed how the people design. Tools for generating images, arranging layouts, and helping with design help creators move faster with lesser efforts. While these shortcuts save the time and boost output, depending on them too heavily raises a fair concern: does easy automation weakens a designer's creativity and problem-solving skills over time?

Traditional design education is hands-on learning where the students repeatedly test their ideas, solve real problems, and build the things. These activities help individuals in development of necessary skills through past judgements and experiences. According to Bjork and Bjork [3], learning the activities, small and intentional challenges during the practices can lead into slow learning down now, but results in long-term memory later. Similarly, Sweller [4] mental workload is the power of brain needed to do a task and automation can reduce this effort which weakens how well people learn and build the skills.

Some previous research show that relying on automation and AI can weaken the mental skills you don't do regularly, making it harder to think independently or fix problems without help. Bainbridge [9] when machines take over our task, we stop practicing and loses key skills. Casner et al. [12] also showed how automation can affect the memory of an individual and mental abilities. Additionally, research on cognitive offloading by Risko and Gilbert [1] suggests that individuals highly depends on external tools to perform mental activities. Latest studies on generative AI have also raised questions about reduced focused thinking and brain exercise [13], [14], [15].

Most research on automation focuses on aviation and office work, leaving a gap in our understanding of how the automated tools affect design students and emerging professionals. Because of this, we know very little about how these tools impact on their long-term retention of practical and critical-thinking skills, or how are they should reshape the way design is taught and practiced. To address this, this study examines how much can designers trust automated tools and how well they can perform foundational tasks on their own. It also tests whether mastering basic design skills before introducing automation helps to people retain those skills over the period of time. By weighing the benefits and drawbacks of these tools, this research advocates for a balanced approach—one where technology supports human creativity rather than replacing core skills..

A. Aim and Objectives

Aim: To study how relying on the automated design tools affects the long-term memory of the basic skills in design students and new professionals.

1. To know the common use of automated assistive tools in the design activities.
2. To see the frequency and level of trust on these tools.
3. To see if people can design without any automated tools.
4. To see if relying on automation can makes people lose their ability to do tasks on their own.
5. To see if learning the basic design skills before using automation helps people in remember those skills better.

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B. Research Gaps

Table 1: Research Gaps

Research gap	Explanation
Field gap	Limited research focuses on automation-related skill decay among design students and professionals.
Outcome gap	Existing AI research primarily examines productivity and creative output rather than independent skill retention.
Timing gap	Limited understanding exists of whether learning fundamental skills before adopting automation improves long-term retention.

C. Research Questions

RQ1: How usually do the design student and early-career professionals use the automated assistive tools, and for which design-related tasks are these tools mostly used?

RQ2: Is there a relationship between the increased dependency on automated assistive workflow and the reduce in practicing design tasks independently?

RQ3: Does learning the practical design skills before the adaptation of automated assistive tools contribute in better long-term memory and practical skill learning?

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Cognitive Load Theory. Sweller [4] argues about working memory is narrow and easily overloaded & splits the mental stress a task demands into natural load, and practical load, the effort given actually builds a mental model or skill, which should be preserved rather than removed [5]. The distinct shows the whole query: a tool that strips practical load is doing what a good design should, but one that also strips maybe removing the very effort that builds skill rather than effort that wastes it.

Desirable Difficulties. Bjork's [6] research on the human memory shows the problems which slows down learning the moment, spacing , restoration practice, also produce stronger long term retention than problems that feel smooth and easy. Bjork and Bjork [3] named it the desirable difficulty and the difference between performance and learning states the studies main concern directly: an automated tool can visibly raise performance while working against the retention that only unaided effort builds.

Cognitive Offloading and the Extended Mind. Clark & Chalmers [7] argue that an external tool relies and is immediately available playing the same functional role a mental process does, can reasonably treated as a part of thinking itself rather than serving only as an aid to this. Risko and Gilbert [1] extent this to a cognitive offloading, the every day habit of shifting mental work on to your device, and show people so readily that to for small games. Sparrow, Liu & Wegner [8] found a strong version of this in the "Google Effect": people who expect later access to information remember it less, because memory is adapted to rely on the internet.

Ironies of Automation and Skill Decay. Bainbridge [9] identified as a paradox in automating skilled work: the more capable an automated system becomes, the less practice its operator gets at the on-going task , leaving them the least prepared exactly when the system fails and hands the control back. Endsley and Kiris [10] describe this as the out of the loop perfomance problem, and Parasuraman and Manzey [11] add automation sarisfaction , a reduced vigilance that comes from trusting a system too consistently. Aviation supplies the best evidence: Casner et al. [12] documented measurable loss in pilot's manual flying skills tied to autopilot uses, and Arthur et al.'s [2] meta-analysis identifies when such skill decays largest, though these findings transfer to design only by paralleling, there's no direct evidence.

Generative AI and Critical Thinking. More recent work surveys extend the concern to the knowledge work. Lee et al. [13] report habitual reliance on generative ai is linked to reduced cognitive effort and confidence in unassisted tasks, Gerlich [14] finds a similar association between AI tool use and acumen. Kosmyna et al. [15], in a study of AI-assisted essay writing reporting what they call "cognitive depth," remain at preprint stage and are noted here as suggestive rather than settled evidence.

How Designers Think, Learn, and Adopt Tools. Within design specifically, Schön's [16] account of reflection-in-action & Cross's [17] work on designing ways of knowing both treat hands –on struggle with a problem as part of how expertise is built, not an ineffectiveness to remove, a claim Ericsson, Krampe and Tesch-Römer [18] support from expertise research generally, where sustained, effortful practice produces skill. Davi's [19]. Technology accepted model, meanwhile explains why designers adopt a tool who in the first place, useful context for why adoption of assistive tools have outpaced study of their effects.

Design-Specific Studies and the Research Gap. A small body of the recent work speaks directly to design practice: studies of de-skilling and cognitive offloading in AI-assisted design [20], of generative AI's impact on design outputs and creative thinking [21], and a review of large language models in UI/UX design [22]. Together with the theoretical lenses above, these sources show that existing evidence on automation-linked skill decay comes mainly from aviation and general knowledge work, while research so far focuses on output quality and workflow rather than the long term retention of foundation skills, the gap this study addresses.

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Table 2: Evidence on Automation and Skill Retention, and the Gap for Design [1]–[22]

Theme	Key idea	Reported effect	Sources	What is missing for design
Cognitive load	Working memory is limited; some effort builds mental models	Removing productive effort can also remove learning	[4], [5]	Not tested with design software
Desirable difficulties	Effortful practice slows performance but aids memory	Easy practice lifts short-term performance more than long-term learning	[3], [6]	Not applied to tool-assisted design tasks
Cognitive offloading	Mental work is shifted to devices and tools	Less information is kept in memory when external access is expected	[1], [7], [8]	No design-specific sample
Automation and skill decay	Operators monitor systems instead of performing tasks	Pilots kept hand-flying skills better than the cognitive skills automation took over; unpractised skills decay	[2], [9]–[12]	No equivalent study in design
Generative AI and knowledge work	AI assistants take over reasoning steps	Greater trust in AI linked to less self-reported critical-thinking effort	[13]–[15]	Visual and creative skills not covered
Design expertise	Skill grows through reflective, effortful practice	Hands-on struggle is part of how designers learn	[16]–[18]	Effect of assistive tools on this practice untested
AI-assisted design	Generative tools in ideation and UI/UX work	Risk of de-skilling raised; studies focus on output and workflow	[20]–[22]	Long-term retention of skills not measured
This study	Assistive design tools	Relationship between reliance and unaided skill	Survey and interviews	Addresses the gaps above

III. RESEARCH DESIGN AND METHODOLOGY

To avoid automated assistive framework. This study adopts various mixed methods and cross-sectional designs [23] An online questionnaire will be distributed to 100 to 150 design students and professionals from all the design field like UI/UX ,product and communication design, selected through purposive and snowball sampling so that we can get opinions of hard to reach or hidden population which will help us empathize with user well by knowing other designer thought process [24] The questionnaire measures participants profile ,frequency of assistive tool generally used, level of reliance on these tools, and confidence performing core design tasks without assistance, using five point Likert items. Six to eight follow-up interviews will explore the reasons behind the survey patterns and thinking. Quatitative data will be analysed with descriptive statistics and correlation to the test the link between reliance and unaided skill, and high , low reliance groups will be compared using t-tests [25] Interview data will be analysed thematically and participants is voluntary, anonymous and will be based on informed consent.so that we get honest survey without the thought of being judged

Table 3: Structure of the Questionnaire

Section	What it measures	Format	Linked RQ
A. Profile	Age, design discipline, years of study or experience, student or professional status	Multiple choice	All
B. Tool use	Which assistive tools are used, how often, for which tasks, and when they were first adopted	Checklist and frequency scale	RQ1, RQ3
C. Reliance	Dependence on tools for ideation, layout, image work and final execution	Five-point Likert items	RQ2
D. Unaided skill	Confidence in performing core design tasks without tools, and perceived change over time	Five-point Likert items	RQ2, RQ3

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Section	What it measures	Format	Linked RQ
E. Views	What designers feel they gain and lose by using assistive tools	Open-ended	Interviews and discussion

IV. PROPOSED FRAMEWORK: THE FRICTION-RETENTION MODEL

Drawing on the theories reviewed in Section II, this study proposes the Friction-Retention Model (Fig. 1) as its conceptual framework. The model treats automated assistance as the independent variable and unaided skill retention as the dependent variable, and explains the link between them through two intermediate stages.

Stage 1: Automated assistance. The designer hands a task such as idea generation, layout or image editing to an assistive tool.

Stage 2: Reduced productive friction. The tool removes the trial, error, recall and decision-making that the task would otherwise demand. Cognitive load theory separates effort that wastes working memory from effort that builds understanding [4], [5]; the model assumes that assistive tools tend to remove both kinds at once.

Stage 3: Less retrieval and deliberate practice. With less effort required, the designer recalls and rehearses the underlying knowledge less often. These are the conditions under which desirable difficulties and deliberate practice would normally strengthen a skill [3], [18].

Stage 4: Lower unaided skill retention. Over time, skills that are rarely practised decline, and cognitive skills appear to be the most exposed [2], [12].

Three moderators are proposed. Prior experience may protect skills that were well learned before a tool was adopted. Design discipline matters because the tasks that are automated differ between UI/UX, product and communication design. The timing of adoption, that is, whether core skills were learned before or after the tool, is the moderator tested directly by RQ3. The model also includes a feedback path: as confidence in unaided work falls, designers may lean on the tool even more, which mirrors the out-of-the-loop problem described in automation research [9], [10].

The model is offered as a set of testable propositions, not as a finding. Table 4 links each stage to the theory behind it and to the part of the questionnaire that measures it.

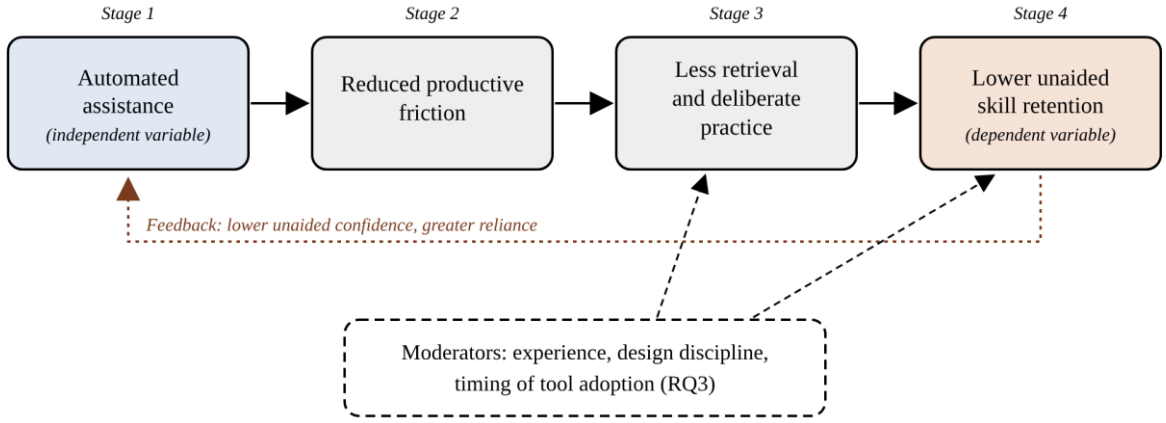

Fig. 1. The Friction-Retention Model (proposed by the authors)

Table 4: Stages of the Friction-Retention Model and How Each Is Measured

Model element	Theoretical basis	Indicator	Questionnaire section	Linked RQ
Automated assistance (independent variable)	Cognitive offloading [1], [7]	Frequency and range of assistive tool use	B	RQ1
Reduced productive friction	Cognitive load theory [4], [5]	Reliance on tools for ideation, layout and execution	C	RQ2
Less retrieval and deliberate practice	Desirable difficulties [3], [6]; deliberate practice [18]	How often core tasks are done without tools	C, D	RQ2
Lower unaided skill retention (dependent variable)	Skill decay [2], [12]	Confidence in core tasks without tools; perceived change over time	D	RQ2, RQ3

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Model element	Theoretical basis	Indicator	Questionnaire section	Linked RQ
Moderators	Ironies of automation [9]; technology acceptance [19]	Experience, discipline, timing of tool adoption	A, B	RQ3

V. DATA ANALYSIS PLAN AND EXPECTED OUTCOMES

Data collection has not yet taken place, so this section sets out how the data will be analysed and which pattern of results would support or challenge the proposed model. No results are reported here.

Data preparation. Incomplete responses and respondents who do not meet the inclusion criteria will be removed. The Likert items [27] in Sections C and D will be combined into a reliance score and an unaided-skill score, and the internal consistency of each scale will be checked with Cronbach's alpha [28] before further analysis.

RQ1: tool use. Frequencies, percentages and means will show which tools are used, how often, and for which tasks, broken down by discipline and by student or professional status.

RQ2: reliance and unaided skill. The relationship between the reliance score and the unaided-skill score will be tested with Pearson's correlation, or with Spearman's rank correlation if the scores are not normally distributed [25]. About 85 respondents are needed to detect a medium correlation ($r = 0.3$) with 80% power at the 5% significance level [29], so the planned 100 to 150 responses are adequate. Respondents will then be divided into low- and high-reliance groups, which will be compared with an independent-samples t-test, or with the Mann-Whitney U test where the assumptions of the t-test are not met [25].

RQ3: timing of adoption. Respondents who learned core skills before adopting assistive tools will be compared with those who began using the tools while still learning, using the same group tests.

Interviews. Transcripts will be coded following the six phases of thematic analysis described by Braun and Clarke [26]: becoming familiar with the data, generating codes, searching for themes, reviewing them, defining and naming them, and writing up. The themes will be used to explain, or to question, the patterns found in the survey.

Table 5 summarises the plan and states, for each question, the result that would support the Friction-Retention Model and the result that would count against it.

Table 5: Analysis Plan and Expected Outcomes for Each Research Question

Question	Variables	Analysis	Result that would support the model	Result that would challenge the model
RQ1	Tool type, frequency of use, task	Descriptive statistics	Frequent use concentrated in core tasks such as ideation and layout	Use limited to minor or finishing tasks
RQ2	Reliance score; unaided-skill score	Pearson or Spearman correlation; t-test or Mann-Whitney U [25]	Significant negative correlation; high-reliance group reports lower unaided skill	No relationship, or a positive one
RQ3	Timing of adoption; unaided-skill score	t-test or Mann-Whitney U [25]	Skills-first group reports higher unaided skill at similar levels of reliance	No difference between the groups
Interviews	Designers' own accounts	Thematic analysis [26]	Accounts of forgetting, or avoiding, tasks without tools	Accounts of tools reinforcing or teaching skills

VI. CONCLUSION, RECOMMENDATIONS AND FUTURE RESEARCH

This paper has set out a study of whether reliance on automated assistive tools is linked to a long-term loss of unaided design skill. The literature reviewed points to a consistent concern: durable learning depends on effort, automation removes effort, and in fields such as aviation the result has been a measurable loss of skill [2], [9], [12]. Recent work on generative AI points in the same direction for knowledge workers [13], [14], yet design students and early-career professionals have rarely been studied. The Friction-Retention Model frames this gap as a set of testable links, and the mixed-methods design provides a practical way to test them. The findings will show how far the concern raised in other fields applies to design.

A. Recommendations

Learn before automating. Design courses should keep foundational tasks tool-free in the early stages, so that skills are built before they are handed to software [3], [18].

Attempt first, then assist. Designers should try a task on their own before comparing their result with the tool's output, which keeps recall and judgement active.

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Tools that explain. Assistive software should offer modes that show the reasoning behind a suggestion rather than only completing the task.

Regular unaided practice. Studios and courses can schedule short tool-free exercises so that core skills stay in use.

These recommendations are provisional and will be revised once the survey results are available.

B. Suggestions for Future Research

The present design is cross-sectional and relies on self-reported skill. Future work should follow the same participants over time and measure skill directly through timed, tool-free design tasks. Experimental studies that assign participants to assisted and unassisted practice would allow causal claims, and comparisons across disciplines and countries would show how far the findings generalise.

REFERENCES

[1] Risko, E.F. and Gilbert, S.J. (2016) 'Cognitive offloading', *Trends in Cognitive Sciences*, 20(9), pp. 676–688. DOI: 10.1016/j.tics.2016.07.002.

[2] Arthur, W., Bennett, W., Stanush, P.L. and McNelly, T.L. (1998) 'Factors that influence skill decay and retention: A quantitative review and analysis', *Human Performance*, 11(1), pp. 57–101. DOI: 10.1207/s15327043hup1101_3.

[3] Bjork, E.L. and Bjork, R.A. (2011) 'Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning', in Gernsbacher, M.A. et al. (eds) *Psychology and the Real World*. New York: Worth, pp. 56–64.

[4] Sweller, J. (1988) 'Cognitive load during problem solving: Effects on learning', *Cognitive Science*, 12(2), pp. 257–285. DOI: 10.1207/s15516709cog1202_4.

[5] Sweller, J., van Merriënboer, J.J.G. and Paas, F.G.W.C. (1998) 'Cognitive architecture and instructional design', *Educational Psychology Review*, 10(3), pp. 251–296. DOI: 10.1023/A:1022193728205.

[6] Bjork, R.A. (1994) 'Memory and metamemory considerations in the training of human beings', in Metcalfe, J. and Shimamura, A.P. (eds) *Metacognition: Knowing about Knowing*. Cambridge, MA: MIT Press, pp. 185–205.

[7] Clark, A. and Chalmers, D. (1998) 'The extended mind', *Analysis*, 58(1), pp. 7–19. DOI: 10.1093/analys/58.1.7.

[8] Sparrow, B., Liu, J. and Wegner, D.M. (2011) 'Google effects on memory: Cognitive consequences of having information at our fingertips', *Science*, 333(6043), pp. 776–778. DOI: 10.1126/science.1207745.

[9] Bainbridge, L. (1983) 'Ironies of automation', *Automatica*, 19(6), pp. 775–779. DOI: 10.1016/0005-1098(83)90046-8.

[10] Endsley, M.R. and Kiris, E.O. (1995) 'The out-of-the-loop performance problem and level of control in automation', *Human Factors*, 37(2), pp. 381–394. DOI: 10.1518/001872095779064555.

[11] Parasuraman, R. and Manzey, D.H. (2010) 'Complacency and bias in human use of automation: An attentional integration', *Human Factors*, 52(3), pp. 381–410. DOI: 10.1177/0018720810376055.

[12] Casner, S.M., Geven, R.W., Recker, M.P. and Schooler, J.W. (2014) 'The retention of manual flying skills in the automated cockpit', *Human Factors*, 56(8), pp. 1506–1516. DOI: 10.1177/0018720814535628.

[13] Lee, H.-P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R. and Wilson, N. (2025) 'The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers', in *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. New York: ACM. DOI: 10.1145/3706598.3713778.

[14] Gerlich, M. (2025) 'AI tools in society: Impacts on cognitive offloading and the future of critical thinking', *Societies*, 15(1), 6. DOI: 10.3390/soc15010006.

[15] Kosmyna, N. et al. (2025) 'Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task', *arXiv preprint*, arXiv:2506.08872.

[16] Schön, D.A. (1983) *The Reflective Practitioner: How Professionals Think in Action*. New York: Basic Books.

[17] Cross, N. (2006) *Designerly Ways of Knowing*. London: Springer.

[18] Ericsson, K.A., Krampe, R.T. and Tesch-Römer, C. (1993) 'The role of deliberate practice in the acquisition of expert performance', *Psychological Review*, 100(3), pp. 363–406. DOI: 10.1037/0033-295X.100.3.363.

[19] Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, 13(3), pp. 319–340. DOI: 10.2307/249008.

[20] Shukla, P., Bui, P., Levy, S.S., Kowalski, M., Baigelenov, A. and Parsons, P. (2025) 'De-skilling, cognitive offloading, and misplaced responsibilities: Potential ironies of AI-assisted design', in *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25)*. New York: ACM. DOI: 10.1145/3706599.3719931.

[21] Fu, Y., Bin, H., Zhou, T., Wang, M., Chen, Y., Lai, Z.G.D.C., Wobbrock, J.O. and Hiniker, A. (2024) 'Creativity in the age of AI: Evaluating the impact of generative AI on design outputs and designers' creative thinking', *arXiv preprint*, arXiv:2411.00168.

[22] Ahmed, A. and Imran, A.S. (2025) 'The role of large language models in UI/UX design: A systematic literature review', *arXiv preprint*, arXiv:2507.04469.

[23] Creswell, J.W. and Creswell, J.D. (2018) *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 5th edn. Thousand Oaks, CA: SAGE.

[24] Etikan, I., Musa, S.A. and Alkassim, R.S. (2016) 'Comparison of convenience sampling and purposive sampling', *American Journal of Theoretical and Applied Statistics*, 5(1), pp. 1–4. DOI: 10.11648/j.ajtas.20160501.11.

[25] Field, A. (2018) *Discovering Statistics Using IBM SPSS Statistics*. 5th edn. London: SAGE.

[26] Braun, V. and Clarke, V. (2006) 'Using thematic analysis in psychology', *Qualitative Research in Psychology*, 3(2), pp. 77–101. DOI: 10.1191/1478088706qp063oa.

[27] Likert, R. (1932) 'A technique for the measurement of attitudes', *Archives of Psychology*, 22(140), pp. 1–55.

[28] Cronbach, L.J. (1951) 'Coefficient alpha and the internal structure of tests', *Psychometrika*, 16(3), pp. 297–334. DOI: 10.1007/BF02310555.

[29] Cohen, J. (1988) *Statistical Power Analysis for the Behavioral Sciences*. 2nd edn. Hillsdale, NJ: Lawrence Erlbaum Associates.

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