

The Cybernetic Teammate

Abstract Examines how AI transforms core pillars of collaboration: performance, expertise sharing, and social engagement through an experiment w/ 776 professionals at P&G. Individuals or teams were assigned to work with or without AI on product development.

Findings: Individuals w/ AI matched performance of teams without AI → AI can replicate certain benefits of human collaboration. AI breaks down functional silos. AI produced balanced solutions while R&D professionals suggested technical solutions and commercial professionals leaned towards commercially oriented proposals. AI prompted more positive self-reported emotional responses among participants, suggesting it can fulfill the social & motivational role of human interaction.

The results suggest AI adoption reshapes performance and how expertise and social connectivity manifest within teams, compelling organizations to rethink the very structure of collaborative work.

Intro

Teamwork -> cornerstone of modern orgs

* 3 fundamental pillars of justification of teamwork:

- ① performance -> teamwork's more effective than individual work, allows for more complex problems to be tackled
- ② Expertise sharing & knowledge complementarity: allows people w/ different expertise to come together & work on the same problem effectively
- ③ Human sociality: people enjoy connecting and increases work motivation.

Foundational challenge: AI (particularly Gen AI) increases individual productivity, creativity, and decision making, its ramifications on teamwork remain unexplored.

QUESTION: Can Gen AI fill the role of humans in teamwork?

Experiment designed to answer these 3 questions:

- ① Does Gen AI provide the performance gains traditionally attributed to teamwork?
- ② Does Gen AI enable a broadening of expertise even when employees lack certain specialized knowledge and skills?
- ③ Can Gen AI offer the kind of social engagement that we typically associate with human collaboration?

Participants were randomly assigned across four conditions:

- ① Control: Individual without AI
- ② Treatment 1 (T1): Team (R&D + commercial)
 - ⊕ AI without
- ③ T2: Individual + AI
- ④ T3: Team + AI

* participants were randomly assigned these conditions, defined by 4 business units:

- Baby care
- Feminine care
- Grooming
- Oral care

* Across 2 geographies

- America
- Europe

* Collaboration occurred remotely through teams, standard P&G practice

* Participants were assigned tasks within their own BUS to develop viable ideas for new products, packaging, communication approaches, or retail execution, etc...

Gen AI tool used: was built on GPT-4 and accessed through Microsoft Azure

Analytical Approach

Regression analysis

$$Y_i = \beta_0 + \beta_1 \text{TeamNoAI} + \beta_2 \text{AloneAI} + \beta_3 \text{TeamAI} + \gamma_{\text{controls}} + \delta \text{FE} + \epsilon$$

Y_i → represents different outcome variables examined in analysis outcomes measure: performance, expertise, and collaboration

Controls: = list of pre-experimental features including demographic and professional characteristics

FE_i → includes day and business unit fixed effects

Primary outcome measure is quality of proposed solution from 1-10
Also measured novelty and feasibility
all on scale 1-10

Expected Quantity $\rightarrow$ binary variable based on survey responses, where participants indicated whether they expected their solution to rank in top 10% (1) or not (0). This measure helps understand how different configurations affect participant's confidence and self assessment.

Measured degree of technicality per solution 1-7 Likert Score assigned by the same human evaluators assessing solution quality

High Score $\rightarrow$ high technicality

Low Score $\rightarrow$ high commerciality

Measured Participants Self-reported

emotional state emotions calculated

pre and post task scale of 1-7

Performance

- Quality scores reveal that both teams without AI and Individuals with AI significantly outperform control group. Their quality distributions are remarkably similar

- $\rightarrow$ evidence that AI can replicate key performance benefits of teamwork

- Teams without AI show quality improvement of 0.24 standard deviations over individuals without AI highlighting the true benefits of collaboration.

- Individuals w/ AI demonstrate 0.37 standard deviation increase

- Teams w/ IA 0.37 increase
 $\rightarrow$ see large productivity improvements
Introducing AI substantially reduced time spent working on solution
teams w/ AI spent 12.7% less time
Individuals w/ AI spent 16.4% less time

→ Non core job employees w/ AI alone achieved performance levels comparable to teams with at least one core-job employee.

↳ Suggests AI can substitute expertise

→ Individuals w/ AI demonstrated a 0.457 standard deviation increase in positive emotions.

→ Teams w/ AI 0.635 increase

→ Both showed significant decrease in negative emotions too.

→ Individuals w/ AI report positive emotional responses that match or exceed those of teams working w/ AI.

↳ AI can substitute some of the emotional benefits

→ Both individuals and teams w/ AI were more likely to generate solutions ranking in top 10% of all submissions.

* Interestingly, while objective performance improved, participants using AI were less likely to expect their solutions to rank in top 10%, compared to control group, suggesting disconnect between actual and perceived performance.

* Overall, AI appears to facilitate more balanced contributions from both technical and commercial perspectives.

Conclusion

AI integration has the potential to reshape the nature of collaboration and expertise in organizational settings.

Artificial Intelligence in PhD Education:

New Perspectives for Research Libraries

Seen from the perspective of library staff working w/ research support in a number of research libraries in Norway.

How research libraries adapt to the development, addresses roles of stakeholders, and proposes measures regarding the support of PhD candidates in the responsible use of AI-based tools.

Intro

* Staff developing AI-based tools are usually the ones defining what's a good explanation of how AI works.

Paper looks into how academic libraries are responding to and adapting to AI tools changing the working methods of scholars and researchers.

Research question: Describe the challenges and opportunities that the advancement of AI pose for PhD candidates, from

the pov of the library staff working with research support in Norway.

Experiment

The workshop used the design method "Six thinking Hats" to discuss following issues/questions:

- How does the use of AI-based tools affect the integrity of the research?
- How should PhD (students) education reflect on AI with regard to academic integrity?
- Where and how can PhD candidates and researchers find reliable info about AI-based services?
- What kind of info and advice can/should be integrated into PhD on track?
- How can PhD on Track - and uni's and academic libraries - address ethical issues that arise in connection with the increasing availability and use of AI-based tools?

The Six Thinking Hats method

Providing six different ways to address a complex problem, considering possible solutions, and tracking progress throughout the thinking process.

The different hats are metaphorically worn by the participants.

*Colors: red, green, yellow, black, white & blue

green → Creative thinker, possibilities

red → instincts, felt dangers/challenges

yellow → Optimist

black → devil's advocate, addressing everything that might go wrong

white → voice of reason, objective and logical way of thinking

blue → Conductor, trying to make the best out of all the ideas emerging

Only used red, green and yellow

Analysis

Reflexive Thematic Analysis → indicates context and given situation as essential acknowledging research subjectivity as not just valid but a resource.

Patterns from qualitative data.

Put together themes in relation to each hat and discuss the relevant data collected.

Findings

57 people participated in the survey

44 work in uni libraries

11 at college libraries

2 at other institutions

AI tools mentioned: ChatGPT, Rayyan, Reenious, Grammarly, Transcribus, Citmaps, Iris, ASReview, and Elicit.

The most significant ethical challenge was bias followed by Plagiarism, cheating, copyright, and co-authorship.

* Participants highlighted ethical concerns related to data security, misinformation, and a loss of critical thinking due to people being "blinded" by good language.

* In addition to ethical aspects, the difficulty in understanding the technology and a lack of resources for training and implementation were considered significant challenges when using AI based tools.

* AI poses challenges in terms of source criticism

* Participants recommend use of "the most general tools" and focus on "limitations of the various tools."

* 6 themes emerged:

- Technology
- Knowledge about AI
- Ethical Issues
- A need for more competence
- The role of the library
- Learning resources

Technology

↳ Challenges due to rapid development
↳ services quickly become out of date
→ where the information comes from
"the English language and American culture characterise the tools, and this might create problems in other languages and cultures"

For opportunities: AI to check quality of data. Automating proofreading, translation, disposition, and summarization of knowledge.

Ethical Issues

- legal aspects and copyright
- Lack of laws and regulations
- Intellectual property, personal data, plagiarism
- Changes to content done in an un-academic way
- Need for transparency in data and quality

For green hat:

"with good guidance in ai, there's a good chance that ethics will become an important component to those who use tools"

A need for more competence

- Understanding possibilities & limitations
- Unpredictable risk of not being updated
- There's so many tools that it's difficult to know what cannot be achieved with them

- problem w/ provenance and what can be trusted with increasing amount of fake news

Role of the library

- Will the library be perceived as an "authority" with "credibility" and "reliability", and what should the "normative" nature of the library resources be?

Learning Resources

- The heterogeneity of the target audience makes it difficult to tailor the learning content to the users.
- Content must be continuously updated
- Invite PhD students to take part in the development

→ Learning resources about AI should "explain how the technology itself works" but also show "opportunities for developing ideas using tools."

→ Focus cannot be purely technical but must also consider perspectives like "learning theory" and scholarly practice"

Conclusion

Education in "transferable" or "generic" skills for PhD candidates has been a part of library services for many years, but now with proliferation of AI the skills become more in demand.

Exploring the Adoption Phenomenon of Artificial Intelligence by Doctoral Students within Doctoral Education

Abstract

Adoption in Academia is an emerging field of interest, but there is scant lit that explores AI adoption by grad students in doctoral education.

4 subthemes

- Adoption Fear
- Adoption Resistance
- Adoption Feasibility
- Adoption Ethics

A balanced approach to adoption depends on development of comprehensive strategies informed by deep understanding of both tech capabilities and human factors involved

Intro

Doctoral students are increasingly adopting a variety of tech to facilitate data collection and analysis and improve communication and collaboration.

Ex°. SPSS, SAS, and R used for Stats.

Nvivo and ATLAS.ti popular for managing, coding, and analyzing qualitative data (interviews, focus groups, textual content).

Zotero, EndNote, and Mendeley assist in managing literature reviews and citations.

In Engineering MATLAB, Simulink, ANSYS are used for experiment simulation and modeling scenarios that are too costly to perform in real life or impractical.

AI integration has potential to transform how research is curated across various disciplines.

On one hand integrating AI tech into research can achieve higher accuracy, improve productivity, and enhance the dissemination and presentation of research findings.

But adoption is hampered by apprehension surrounding use uncertainty, lack of guidance, scholarly resistance, and potential ethical implications.

Could cause excessive dependence on tech, diminishing the crucial human elements of education and learning.

Potential impact on the rigor and integrity of doctoral education.

Research Questions

- ① How do doctoral students perceive the benefits and challenges of adopting AI tech into their academic research and coursework?
- ② What factors influence the readiness and apprehension of doctoral students toward integrating AI technologies into their doctoral education?

Background

Participants are enrolled in Human Resource Development (HRD) doctoral program or possess a doctorate in HRD.

In doctoral education students use various AI tools to enrich their coursework. TensorFlow and PyTorch are prominent machine learning libraries that empower the creation of intricate AI models for applications like natural language processing and computer vision.

Jupyter Notebook provides an interactive platform for data visualization and analysis, which is crucial for data science projects. ChatGPT aid in content generation and idea brainstorming, while GitHub Copilot assists in software development by offering code suggestions. Apps like Grammarly and Turnitin ensure quality and originality of written work.

Emerging research suggests AI adoption by grad students can enhance their learning experiences, drive innovative research, and contribute to advancement of knowledge in respective fields.

The effectiveness of AI technology in delivering truly personalized learning experiences remains unexplored, particularly in accommodating diverse learning styles and backgrounds.

Research on the best practices to incorporate AI tech into medical curriculum is sparse.

Should focus on integrating AI without overwhelming the current curriculum.

Method

In Cat (collaborative autoethnography -> research method that allows participants to explore personal experiences within cultural context while also reflecting on the collective experience) participants function as primary peer reviewers for each other, facilitating group discussions, identify common themes, and

explore differences.

Data Collection

① Each participant conducted a pre-writing exercise, prompted to describe their experiences using AI tech in doctoral studies. Instruction to focus solely on articulation of their experiences, disregarding concerns related to content coherence, structural organization, grammatical accuracy, and adherence to scholarly conventions.

② participants shared narratives w/ one another to facilitate group discussion. Collaboratively identified key phrases and concepts.

③ After guiding facilitator tabled the process codes, they were reviewed by each participant and follow-up questions were generated to probe deeper into key relationships between

between process codes. Systematically organize relationships into descriptive categories.

④ Make sense of the descriptive categories by referring back to study's intent. Interlinking themes with educational outcomes and institutional goals. Researchers aimed to explicate final themes, each one critically evaluated for its capacity to offer comprehensive insights into AI adoption process.

⑤ Each of the final themes were discussed via group email to ensure clarity and consensus among research group.

Findings

Reflections highlighted general uncertainty regarding the adoption of AI tech within doctoral studies.

Initial Process Codes from Reflection

Codes: initial skepticism, practical applications, ethical concerns, technological dependence, AI in academic context, efficiency and precision, ethical implications, transformative potential, emotional responses, learning curve, integration challenges, collaboration and discourse

Structure Relationships from Process codes into Descriptive Categories

- AI adoption concerns → Initial Skepticism, Ethical concerns, Integration challenges
- AI Operational Dynamics → tech dependence, Efficiency and precision, Learning curve
- AI impact and potential → practical applications, transformative potential, AI in academic context.
- Human-AI interaction and response → emotional responses, collaboration & Discourse
- Ethical & Philosophical considerations → ^{ethical} inspiration?

Unknown impacts and potential ethical dilemmas associated with AI techs are significant contributors to adoption fear.

→ Doctoral students may be anxious about how AI technology could affect their academic practices and future career prospects.

→ Integration challenges often lead to adoption resistance among students and faculty, who may feel that AI tech doesn't fit well w/ existing practices or values.

→ If the tools are perceived as overly complex or disruptive students and educators are more likely to resist integrating them into workflows.

→ Doctoral students who see operational benefits are more likely to view AI as a valuable asset to their academic pursuits.

Discussion

Primary overarching theme: Adoption Strategy

4 distinct subthemes: adoption fear, resistance, feasibility, and ethics.

→ ADOPTION STRATEGY

AI adoption strategies have been considered for teaching AI, curricular development and design, learning analytics, and for automating administrative processes.

This is mostly a psychological activity. Behavioral examples include: research planning, resource leveraging, self-regulated learning, and time management.

→ Students are concerned for how professors will perceive their work if they implement AI.
"Would they see it as a shortcut, something that undermines the hard work we put into our research? That fear made me hesitate to fully explore what AI could do for me academically!"

→ Expressed concern over whether AI integration inadvertently diminishes student abilities to analyse and evaluate info independently.

Adoption Resistance

→ Fears of developing dependency on technology

→ Unfamiliarity with AI can lead to adoption resistance as students may perceive the learning curve as steep and the risk of

academic failure high

→ Faculty skepticism: "Some of my professors are really skeptical about AI. They worry it might undermine the critical thinking skills we're supposed to develop. If people teaching us aren't onboard, it's hard to feel confident about using these tools ourselves."

→ Legitimate concern about quality and utility of AI. The fact that AI generated texts tend to be less factual and constructive could reinforce existing doubts about ability of AI tech to match or enhance depth or rigor of human effort in academic evals.

→ "Educators are willing to adopt new tech if they believe students learn better when they are engaged w/ tech."

Adoption feasibility

- > The adoption process is typically initiated w/ recognition of a specific academic or research need.
- > Pilot testing on a small scale
- > Concern for compliance w/ institutional guidelines
 - ↳ guidelines sometimes are unclear
- > "Some professors are all for using AI while others are totally against it. This makes it hard to know what's acceptable and what's not"

Implications for Practice

- > Aligning institutional goals and student learning objectives
- > Integrating AI tech in a way that complements existing skills

rather than replacing them.

- > Making guidelines transparent and accessible.

- > Establishing support systems

Implications for Research

- > More empirical research is needed to evaluate the efficacy of AI.
- > Evaluate potential cognitive downside

Conclusion

AI adoption strategies should address doctoral student concerns regarding fear, resistance, feasibility, and ethics.

Navigating Cognitive Dissonance: Master's Students' Experiences with ChatGPT in Dissertation Writing (2025)

Abstract

- > understanding AI impact on student's psych during dissertation writing
- > identify strategies they use to manage dissonance
- > strategies: improving prompt quality, feeding relevant domain-specific data to the AI, avoiding academic misconduct, and maintaining academic integrity

Intro

- > Blurred boundaries between AI-assisted writing and plagiarism introduce ethical dilemmas for both students and institutions

*cognitive dissonance: psych discomfort resulting from conflicting beliefs, attitudes, or behaviors.

-> dissonance may occur when students rely on tools like ChatGPT to enhance their theses while simultaneously perceiving this behavior is misaligned w/ academic norms or personal values.

-> China students using ChatGPT in their thesis writing

-> studies have shown dissonance can lead to emotional reactions such as guilt, regret or frustration.

Research questions

① What specific cognitive dissonance processes do master's students experience using ChatGPT in thesis writing?

① What strategies do students employ to manage cognitive dissonance while using chatGPT?

Research Context

- Universities in mainland China
 - ↳ Master students required to write thesis
- 20 students across 3 universities

Sampling Method

- grounded theory
- employed theoretical sampling

Data Analysis

- Interview transcripts imported to NVivo 14 for coding analysis

Definitions for coding processes

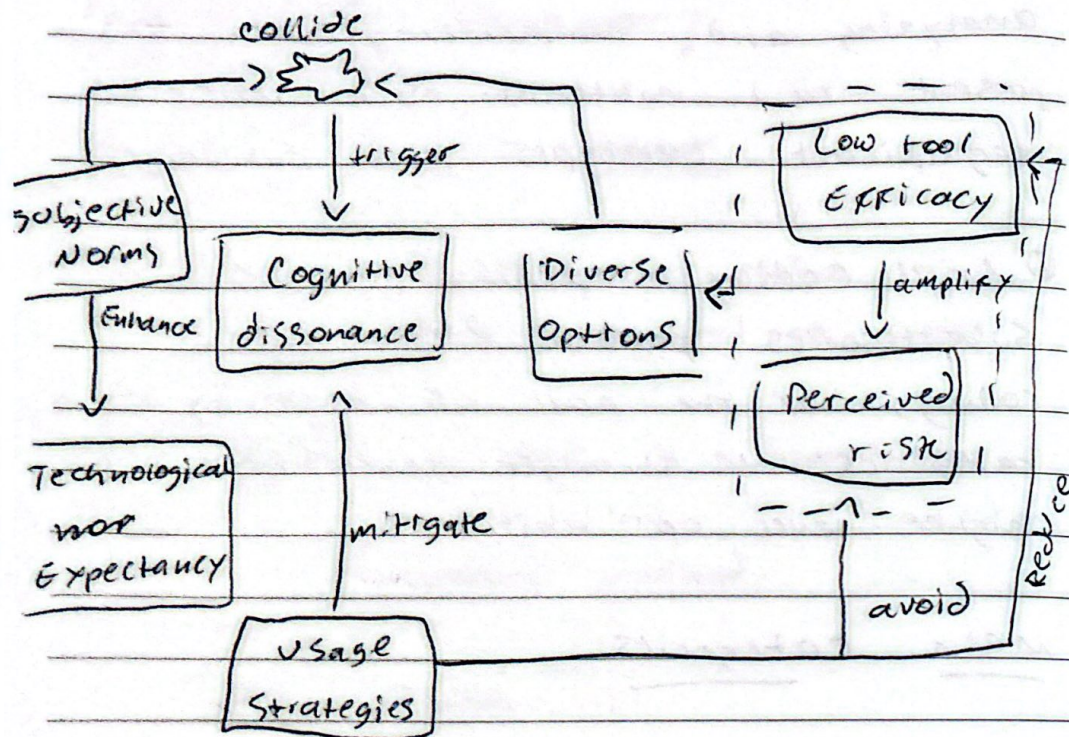
① Open Coding: process of meticulously analyzing and summarizing data to present raw material as a series of significant concepts and categories.

② Axial Coding: refining numerous subcategories formed during open coding, w/ the goal of obtaining main categories w/ stronger generalizations or higher level of abstraction.

Main Categories

Subjective norms, usage strategies, low tool efficacy, diverse options, perceived risk, technological expectancy

③ Selective coding: further analyze main categories, identify a core category of overarching significance and connect all categories to it.



In this model subjective norms and technological expectancy drive master's students to use ChatGPT in thesis writing. However, this intention is challenged by low tool efficacy and perceived risk, prompting some to consider alternatives. The clash between

external pressures and usage barriers creates a cognitive dissonance. In response students adopt various usage strategies to alliviate the discomfort.

Triangulation for validating ~~the~~ findings

- > Interviewed 3 experienced master's thesis supervisors
- > Findings were consistent with the patterns identified in student data

Research Results & Discussions

Positive promotional effects, supervisor support, and clear institutional norms enhance students' tech expectancy of ChatGPT, making them more willing to use it in thesis writing.

Epistemic Dialect Engine

Literary Review Resume

After reviewing several recent studies examining the role of AI in doctoral education, research and collaborative work the literature suggests that AI is not being used as a replacement for the professors, rather as complementary tools that exist along in a continuum of support roles include

① Supplement to Faculty expertise
Activities such as

lit searches, drafting & editing, coding, stat analysis, qualitative coding, reference management, brainstorming, programming, data visualization and administrative tasks

② Tutor and learning scaffold

Individualized tutor
Activities: explain difficult concepts, provide immediate feedback, assist brainstorming, organize ideas, improve writing, support self-regulated learning, help students navigate complex research tasks

③ Collaborative Partner

The Cybernetic Teammate
Collaborator capable of participating in human problem solving

- Individuals working w/ AI performed similarly to teams working w/ AI
- AI broadened access to expertise
- AI reduced functional silos
- Participants produced more balanced solutions
- Productivity increased while completion times decreased
- Emotional responses comparable to human collaborations

Persistent Faculty and Institutional Concerns

→ Academic integrity, plagiarism, hallucinations, bias, copyright, data privacy, transparency, declining critical thinking, excessive tech dependency, inconsistent institutional policies, and uncertainty surrounding acceptable AI use

Several qualitative studies found that both students and faculty worry AI could undermine the development of independent scholarly reasoning if integrated without clear pedagogical objectives.

Researchers recommend institutions establish transparency policies, improve AI literacy, and develop ethical guidelines before expanding AI integration.

Conclusion

Faculty are adopting AI selectively

- Research support
- Writing assistance
- Coding
- Data analysis
- Administrative efficiency
- Personalized student support

Danko suggestions

→ Cognitive processes
getting better or worse?
Deeper emotional connection?

→ What happens in the invisible side of learning?

→ AI could watch if this is happening and a survey at the end

→ Come up w/ survey questions

Questions to follow up on

Herdling

- Best institutional holdings database?
- Best retail investor dataset?
- Weekly holdings available
- Best news-event identification method
- Event study methodology?

AI

Has anyone measured cognitive transformation while students collaborate with AI?

- How is metacognition measured?
- How is transfer measured?
- How is self-regulation measured?
- Can AI itself administer cognitive assessments?
- Can AI detect learning in real time?

Metacognition

What's metacognition? Why does it matter? How do researchers measure it? What instruments exist? What are criticisms?

Evaluating metacognitive self-reports

Systematic reviews of the value of self-report in metacognition research

• What's metacognition?

- Comprises both the ability to be aware of one's cognitive processes (metacognitive knowledge) and to regulate them (metacognitive control).

- Thinking about thinking

- Ability to monitor one's cognitive processes

• Why does it matter?

- It plays an important role in learning and education

- High performers tend to present better cognitive abilities and control in diverse educational activities.
- Critical to improve education

* How do researchers measure it?

- Cognitive neuroscientists investigate via behavioral tasks
- Educational neuroscientists rely on introspective questionnaires.

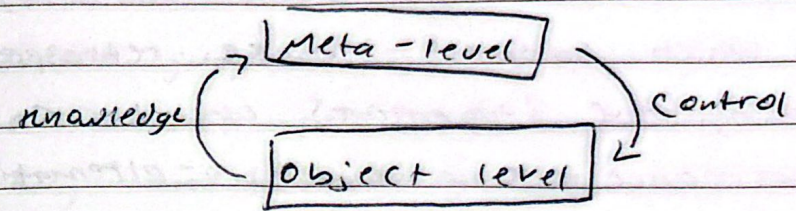
° Self-Regulated Learning theory (SRL)

* What are criticisms?

- Recurring issues that impede the relevance of neural insights for educational practices concern external validity, theoretical discrepancies and differences in terms of the domains of metacognition operationalised.

→ SRL is constrained to learning activities usually in educational settings.

* What is metacognition?



Meta-knowledge is characterized as the upward flow from object-level to meta-level. Meta-control is characterised as the downward flow from meta-level to object-level. Metacognition is therefore conceptualised as the bottom-up monitoring and top-down control of object-level processes.

→ Meta-knowledge: Knowledge individual has of their own cognitive processes and ability to monitor & reflect on them.

→ Metacognitive Control: self-regulatory mechanisms such as planning and adapting behavior based on outcomes.

How do researchers measure it?

- Neuroscientists have used paradigms in which subjects make retrospective metacognitive judgements on their performance in a two-alternative forced choice task (2-AFC).

- In 2-AFC's subjects are asked to choose which of 2 presented options has the highest criterion value. Different domains can be involved such as memory and perception.

- Ex: Subject may be instructed to visually discriminate which one of 2 boxes contains more dots, identify higher contrast Gabor patches, or recognise novel words from words that were previously learned. The subjects engage in metacognitive judgements by rating how confident they are relative to their decision in the task. Based on responses one can evaluate subject's metacognitive sensibility (the ability to

discriminate one's own correct and incorrect judgements), metacognitive bias (the overall level of confidence during task), and metacognitive efficiency (level of metacognitive sensibility when controlling for task performance).

* What instruments exist?

- Commonly used methods to assess metacognitive sensibility during retrospective judgements are the receiver operating curve (ROC) and meta-d'.

- Both derive from signal detection theory (SDT)

- Brain imaging methods (MRI, fMRI)

- Transcranial magnetic stimulation

* How do researchers measure it?

- Metacognitive judgements

- EF $\rightarrow$ behavioral tasks such as: flanker task, Stroop tasks, motion discrimination tasks, and demand selection tasks

* What are criticisms?

• One major limitation of current research is ecological validity. It's unclear to what extent the operationalisations reviewed above reflect real-life metacognition. For instance, are people who can accurately judge their performance on a behavioral task also able to accurately assess how they performed during an exam? Are people with higher levels of error regulation & inhibitory control able to learn more efficiently?

-> A solution for improving validity may be to compare operationalisations of metacognition in cognitive neuroscience with the ones in educational sciences, which have shown clear links with learning in formal education. This also applies to metacognitive training.

* What are the tools?

- Self-report questionnaires
- Interviews -> hypothetical situation questions
- learning journals
 - thinking aloud protocols
 - > write about learning experiences and thoughts on learning
 - > verbalise thoughts while performing a problem-solving task
- > widely used questionnaires
 - Metacognitive Awareness Inventory (MAI)
 - MSLQ
 - CASSI

-> A recent meta-analysis reported a weak correlation of self-report questionnaires and interviews with academic performance whereas think-aloud protocols correlated highly.

-> Several studies suggest that learning journals can positively enhance metacognition, higher metacontrol & metaknowledge

Transfer of Learning

* Questions: what is transfer? near transfer vs far transfer. How do researchers test transfer? How long after learning do they measure it? What tasks do they use?

National Research Council, Teaching and Assessing for Transfer

* What's transfer?

- Defining characteristic of deep learning

* How do researchers test transfer?

-> Design of instruction for transfer should start with clear delineation of the learning goals and a well-defined model of how learning is expected to develop.

-> Designing measures to evaluate students' accomplishments can be important

Starting point. Outcome measures can provide concrete representation of student learning performance.

Evidence-based approach to assessment rests on 3 pillars

- Model of how students represent knowledge and develop competence in a domain.
- Tasks or situations that allow one to observe student performance relative to the model
- An interpretation framework for drawing inferences from student performance

* What task do they use?

- Computerized problem-solving component of the Programme for International Student Assessment (PISA)

27-40 min test. Difficulty of items is manipulated by increasing the # of relationships that the test taker has to deal with.

-? This PISA framework defines

- ① info retrieval
- ① model building
- ③ forecasting
- ④ monitoring and reflecting
- Scoring for the model building reflects whether the test taker generates a correct model or the problem.
- Scoring is based on whether test taker has set and achieved target goals.
- Points awarded for monitoring and reflecting which include checking goals at each stage, detecting unexpected events and taking remedial action.

* (Another assessment example is
3 multi-state examinations)

* What is transfer?

- Learning in one context affecting performance in another.
- Extent to which knowledge, skills, and abilities are applied, generalized, and maintained over time.

* Near transfer vs transfer

- provide the standard distinction, and how to judge "near" transfer across multiple dimensions instead of treating it as a single yes/no label.

* How do researchers test transfer?

- The NRC Chapter describes evidence based assessment with a learning model, tasks that let you observe performance, and an interpretation framework; it gives examples such as PISA problem-solving, licensing exams, and simulation-based performance assessments.

* How long after learning do they measure it?

• The NRC chapter notes that studies often measure immediately after instruction, but follow up periods vary; one review cites found an average follow-up of 92 weeks for some social-emotional learning studies.

* What tasks do they use?

• Common tasks include novel problem solving scenarios, simulated cases, performance tasks, comparison simulations, and work like applications that require learners to apply the same underlying principle in a new surface context.

Conceptual understanding

questions?

- What separates memorization from understanding?
- How do instructors evaluate conceptual change?
- How do misconceptions get measured?

How can teachers assess students' conceptual understanding?

Conceptual understanding is not just "knowing facts"; it shows up when a learner can connect ideas, explain why something is true, transfer it to new situations, and monitor their own thinking. Memorization is usually narrower, it can support learning, but on its own it often produces correct recall without robust explanation or application.

* What separates memorization from understanding?

The clearest distinction is memorization stores information, while understanding organizes knowledge so it can be used flexibly.

* How instructors evaluate conceptual change?

Instructors evaluate conceptual change by looking for movement from a student's initial explanation toward a more scientific one, usually across time and across task.

* How misconceptions get measured?

Misconceptions are usually measured indirectly, by designing items that make common incorrect ideas visible.

* A simple way to think about it

• Memorization answers "what is it?"
understanding answers "how does it work and why?"

Self-Regulation

Questions

- What is Self-regulated learning?
- How do researchers measure planning?
- Monitoring?
- Evaluation?

Self Regulated Learning Questionnaire reliability and validity Study

What's self-regulated learning?

Constructivist process in which students set goals/objectives for learning at 1st, and then, regulate their cognition

and behaviors and also control these.

- It's a self-regulated process from which learners benefit in order to convert their mental abilities into academic skills.

- Activity students implementally do for themselves, not an inherent one.

Strategies to gain self-regulation

- Metacognitive strategies for the planning, following and alteration of cognition
- Cognitive strategies such as repetition, interpretation and ...
- Self-regulated learning skills scale^s and the interview form in order to make a description of the self-regulated learning skills of medical school students and to examine their self-regulating learning skills according to their success level.

- Motivated strategies for learning questionnaire (MSLQ)

- Self-regulated learning scale and self-regulated learning support scale

Experiment

- Study for validity and reliability of Self-Regulated Learning Questionnaire (SRLQ)

- Test ended in 64 obtained items. Items were graded according to 5-point likert-type, as "never = 1", "seldom = 2", "sometimes = 3", "usually = 4" and "always = 5".

Findings

- Kaiser-Meyer-Olkin value was 0.945 which is fair

- Bartlett test was $\chi^2_{(532)} = 7320.964$
 $p < .01$

- Cronbach's alpha value is 0.94 reliability is quite high

- Confirmatory Factor Analysis (CFA) used to test whether data available to the researcher is compatible with the previously constructed factor structure.

- Root Mean Square Error Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI) values, which are model fit measures, were taken into consideration. In the validated fluid factor analysis, the fit index of the five-factor model of the self regulated learning questionnaire was examined.

Experiment Findings

- It was determined that the t value for the items in the questionnaire changed between 55.28 and 114.48. According to this, all values obtained in the first level confirmatory factor analysis were found to be significant at 0.5 level.

- 2nd level CFA determined RMSEA value as 0.035 and SRMR value was 0.047, which are required to be below 0.05 in case that the model fit is ensured.

- GFI value was 0.88; AGFI was 0.87; CFI 0.98, and NFI 0.94. The acceptable fit of these values was 0.98 (and ~~NFI value was 0.94~~).

→ This indicates that construct validity of the questionnaire is confirmed.

Reflection

questions

- How is it defined? Reflection w/ critical thinking, reflection scales, reflection journals

"Defining Reflection? Another look at John Dewey and Reflective Thinking"
Reflection in learning - Flip education -> metacognition

Dewey and Reflective Thinking

- What's reflection?

-> Reflection in learning is the deliberate cognitive process of examining experience to construct meaning. Research shows it deepens understanding and builds self-regulated learners.

- Reflection is a deliberate "interrogation" of an experience, not a simple summary or review of what happened.

- Brief frequent reflection (2-5 mins) immediately following a task is more effective than long, delayed assignments

- Must be scaffolded w/ specific prompts like "I used to think... now I think..." to move students past surface level descriptions
- Reflection must include emotional component, helping students identify where frustration or surprise signaled a shift in their understanding.

"A Four Category Scheme for Coding and Assessing the Level of Reflection in Written Work"

① Non-reflection

- The answer shows no evidence of student attempting to reach an understanding of the concept or theory which underpins the topic
- Material has been placed into an essay without the student thinking seriously about it, trying to interpret the material or forming a view.

- Largely reproduction, with or without adaptation of the work of others.

② Understanding

- Evidence of understanding concept or topic
- Material is confined to the theory
- Reliance upon what was in the textbook or the lecture notes
- Theory is not related to personal experiences, real-life applications or practical situations

③ Reflection

- Theory is applied to practical situations
- Situations encountered in practice will be considered and successfully discussed in relationship to what has been taught. There will be personal insights which go beyond book theory

④ Critical Reflection

- Evidence of a change in a perspective over a fundamental belief or understanding of a key concept or phenomenon
- Critical reflection is unlikely to occur frequently

Conclusions

- Scheme is applicable to a range of reflective works such as journal entries, essays, and ~~(contributions)~~ contributions to online discussions
- Users need to be familiar with the four categories
- Judgements should be holistic and reflect the highest level of reflection observed
- Some work may fall between 2 categories
- Categories can be used as A, B, C, D grading scheme

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- this scheme is a useful complement to the SOLO taxonomy and can be used in conjunction with discipline specific criteria

Reflection vs Critical thinking.

- reflection is a process that can generate critical thinking, but they are not the same

Reflection journals

- Journal entries give reflection a cumulative structure
- Prompt students with questions that escalate in depth
- Early entries describe and respond to experience, later entries evaluate assumptions, identify patterns in their own thinking, and consider how their perspective has changed.

Connection to active learning

- Reflection is not an add-on to active learning; it's the mechanism by which active learning produces durable understanding.
- Without a reflective component, activities engage students physically and socially but may not consolidate learning at the conceptual level.
- The Kolb's Experiential learning cycle: concrete experience and active experimentation generate the raw material for learning, but reflective observation is what converts that material into abstract conceptualization.

Metacognition and reflection

are deeply intertwined: metacognition is the capacity to monitor and regulate one's own thinking, and reflection is the primary tool through which that capacity is exercised and developed. Self-regulated learning depends on

reflection at every stage of the regulatory cycle: learners set goals, monitor progress, evaluate outcomes, and adjust strategy. Without structured reflection practice, students lack the self-knowledge to regulate effectively, and self-regulation frameworks remain theoretical rather than operational.

Cognitive Growth

- Researchers usually define cognitive growth as change over time in knowledge, skills, reasoning, or related competencies.
- In higher education "learning gain" (or performance) is often used as the closest umbrella term, and is commonly defined as improvement made during time in college or university.

How is growth defined?

- The literature shows at least 3 common ways to define growth.
 - ① Treat it as "distance travelled" meaning the difference between a learner's status at two points in time.
 - ② Value added, comparing actual performance with performance predicted from starting point to prior attainment.
 - ③ Improvement in knowledge, skills, work readiness, and personal development.

Development or Performance

- Growth is a change in knowledge, skills, or competencies over time.
- It is often measured longitudinally but can also be estimated with prepost or value added models.
- Developmental in concept since it concerns change in capability and understanding.

- It is performance based in measurement, because researchers frequently rely on assessments, rubrics, or test scores.

Learning Assessment Instruments / Tools

Tool	What it measures	Format/Use
MAE	Metacognitive awareness, with broad dimensions such as knowledge of cognition and regulation of cognition	Self-report questionnaire
MSLQ	Motivation & learning strategies in college students, including value, expectancy, affect, & strategy use	Self-report questionnaire, commonly 81 items or an abbreviated form
CAT	Classroom Assessment Techniques family, used for quick feedback on learning and teaching	Short format, often informal

Tool	What it measures	Format/Use
Concept inventories	Domain-specific diagnostic tests of conceptual understanding & common misconceptions	Usually multiple choice or similar diagnostic items
SOLO taxonomy	A framework for classifying the quality & complexity of observed learning outcomes	Rubric / taxonomy for scoring work or outcomes
Bloom's taxonomy	Framework for organizing learning objectives by cognitive complexity	taxonomy used to write outcomes & assessments
Reflective Thinking Questionnaire	Measures levels of reflective thinking, including habitual action, understanding, reflection & critical reflection	Self-report questionnaire
SRL interview schedule	Elicits self-regulated learning strategies through interview responses	Semi-structured interview

Best use cases

- MAI: use when you want a broad self-report of metacognitive awareness
- MSLQ: use when you want motivation plus learning strategy data, especially with college students
- Concept inventories: use when you want to diagnose conceptual understanding in a specific discipline
- SOLO: use when you want to rate the complexity of student work or align assessment with depth of understanding
- Bloom's: use when you want to write objectives or ensure coverage across cognitive levels
- Reflective thinking questionnaire: use when reflective thinking is the outcome of interest
- SRLIS: use when you want richer evidence about actual self-regulated learning behaviors than a question alone can provide.

Options

- Self-report questionnaires: MAI, ~~MSQ~~ MSLQ, Reflective Thinking Questionnaire
- Interviews: SRLIS
- Diagnostic test: concept inventories
- Taxonomies/rubrics: SOLO, Bloom's
- Classroom feedback tools: CAT