Decrypting Log Data: A Meta-Analysis on General Online Activity and Learning Outcome within Digital Learning Environments

Research Synthesis & Big Data | Virtual Conference

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WHY “DECRYPTING LOG DATA”?

- Need for online learning increased drastically (Ali, 2020)

- Only little is known about how
  - Students use online classes
  - Their online learning behavior is linked to learning outcomes

- Possibility to analyze automatically tracked log data from students’ interactions with the online learning environment (Gašević et al., 2016)

⇒ How useful are broad log data indicators for the evaluation of online classes?

⇒ Can broad log data indicators be used as a predictor for learning outcomes?

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GENERAL ONLINE ACTIVITY AND LEARNING OUTCOMES

- Systematic reviews about the **value of broad log data indicators** are missing

- **Total login time** and **login frequency** are commonly used as log data indicators to measure general online activity linked to students' achievement (You, 2016)

- However, there is a **debate on the type of log data suitable** to serve as a measure of learning behavior (Agudo-Peregrina et al., 2014)

⇒ **Inconsistent findings** on the association between indicators of general online activity and learning outcome (e.g.: Broadbent, 2016; Conijn et al., 2017; Strang, 2016; Wang, 2019)

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THE PRESENT STUDY

Does a relationship exist between general online activity and learning outcome?

- **Meta-analytic approach**: pooled correlation between…
  - General online activity (i.e. total login time vs. login frequency)

  and
  - Learning outcome (i.e. course grade or course score)

- **Moderators**:
  - Course format (blended vs. online)
  - Discussion board usage (instructed vs. not instructed)
  - Requirements (graded online activities vs. none)
  - Operationalization of general online activity (total login time vs. login frequency)
  - Publication year

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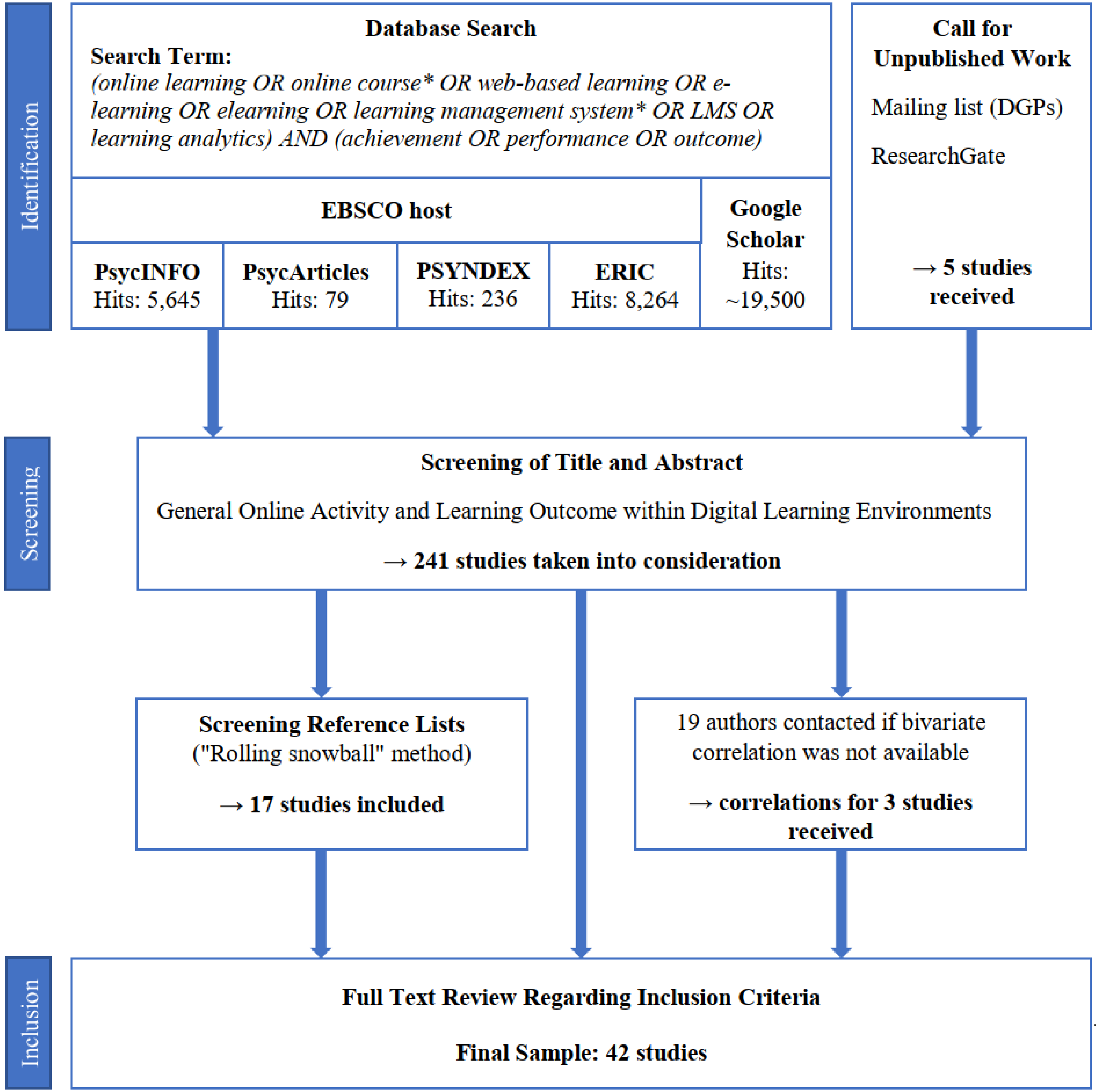
METHOD –
LITERATURE SEARCH



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METHOD – STUDY SELECTION: INCLUSION CRITERIA

1. **Digital learning environment** (i.e. LMS, online university course) as setting
   a) Fully online formats vs. blended learning formats
   b) Institutional courses
2. **Measure of general online activity**, operationalized as **total login time** or **login frequency**
3. **Measure of learning outcome**, operationalized as **course grade** or **course score**
4. Sample comprising **(university) students**
5. Publication year of the study between **1969** (first connection of the internet) and **2021**
6. Language of publication: **English, German**
7. Report of **correlations** between general online activity and learning outcome

METHOD – EXCLUSION CRITERIA

1. Measure of general online activity through **self-report** methods

2. Measure of general online activity through **single activities**

3. **Commercial e-learning courses** as setting

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METHOD – CODING AND STATISTICAL ANALYSES

- Development of a **standardized coding protocol**
- **Double coding** by two independent raters: Cohen's (1960) $\kappa = .91$

- **Effect size:** Pearson product-moment correlation
- **Meta-analytic model:** three-level random-effects model with a maximum likelihood estimator (Cheung, 2014; Viechtbauer 2010)
- **Sensitivity analyses**
  - Studentized deleted residuals (Viechtbauer & Cheung, 2010) to identify extreme correlations
  - Robustness check: removing three particular studies that differed in their conceptualization
- **Publication bias:**
  - Meta-regression: ES from peer-reviewed vs. not peer-reviewed sources (Harrer et al., 2019)
  - Rank correlation test (Begg & Mazumdar, 1994)

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RESULTS – DESCRIPTIVE STATISTICS

Meta-analytic database	
# of effect sizes	106
# of studies	42
# of independent samples	70
Overall *N*	29,648
Publication year	between 1997 and 2021
Publication type	74% peer-reviewed article 5% doctoral thesis 21% conference paper

Course description	
Format	24% online 73% blended
Duration	between 6 and 19 weeks (*Mdn* = 12 weeks)
Discussion board usage	18% instructed 79% not instructed
Requirements	44% graded online activities 55% none
Operationalization of general online activity	44% total login time 56% login frequency

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RESULTS – META-ANALYTIC MODEL

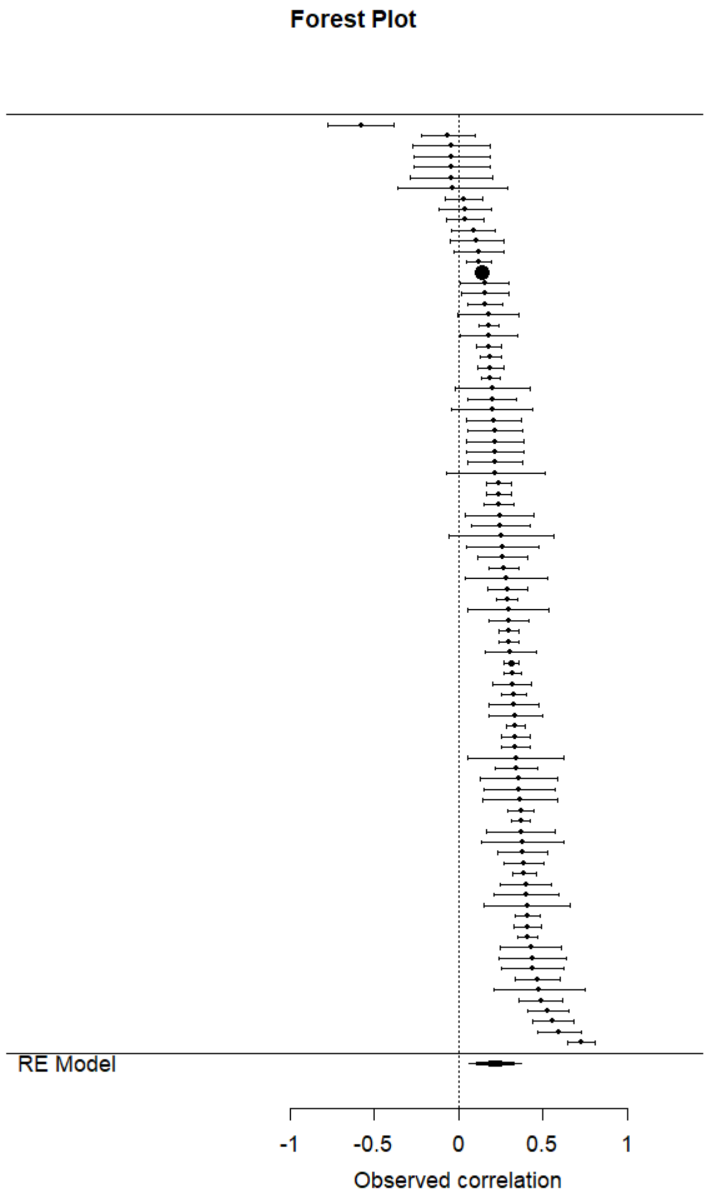
- Overall pooled correlation of **ρ = .24**,
  p = .002, 95% CI (.06, .38)

→Students who are more active online, have the better learning outcome

- Meta-regression and separate moderator analyses:

→ None of the moderators was significant and the five moderators explained only 0.44% of the random variance

- Sensitivity analyses – after eliminating nine extreme correlations from the database, the pooled effect remained at **ρ = .24**. Solely the 80% CRI decreased from [-.10, .59] to [.04, .43]



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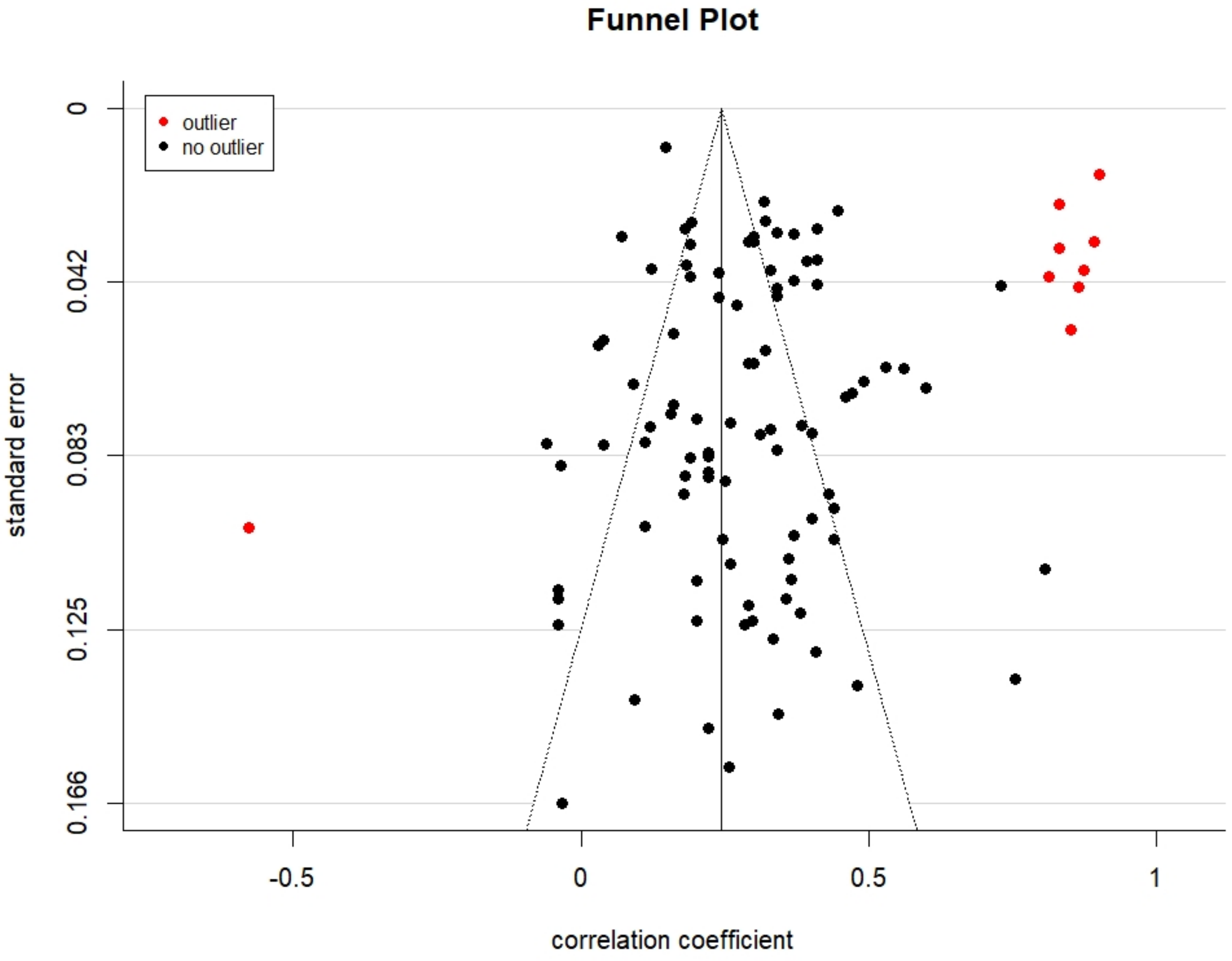
RESULTS – PUBLICATION BIAS

- Meta-regression (ES extracted from peer-reviewed vs. not peer-reviewed sources)

→ No significant difference (γ = -0.04, *SE* = 0.12, *p* = .72)

- Rank correlation test

→ Indicated a symmetric funnel plot (τ = .01, *p* = .90)



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SUMMARY

- We identified a small – yet statistically significant – pooled correlation of **ρ = .24** between general online activity and learning outcome.

- This effect remained **robust** across sensitivity analyses.

- However, the meta-analytic model revealed **high heterogeneity** between studies that could not be explained by moderator analyses.

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MODERATOR VARIABLES

Limitations of the included moderators

- Moderator variables were restricted to broad course characteristics
- Lack of information on contextual variables (Gašević et al., 2016) reported in primary studies

Potential other moderators

- Overall structure offered by online courses
  - Instructional design (Lust et al., 2012)
  - Shares of synchronous methods and applications (Kinshuk & Chen, 2006)
  - Online assessments (Knight, 2020)
- Incentives to ensure students' participation (gamification, e.g. Hamari, 2017)
- Distribution of online activity across the course duration (Dunn et al., 2013)

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IMPLICATIONS FOR FUTURE RESEARCH

- Standardized procedure to take methodological quality of log data studies into account (Scheffel et al., 2014)
- Open data movement as a promising development (Gurevitch et al., 2018)
- Multi-level analyses based on raw data (IPD, Kaufmann et al., 2016)
- Informal learning as a promising extension

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THANK YOU FOR YOUR ATTENTION!

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