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Impact of microlearning on academic performance of students in higher education: A systematic review and meta-analysis

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Abstract

Microlearning is an innovative pedagogy which is the process of learning through small-sized, well-planned learning units and short-term learning activities. The objective of this study was to conduct a systematic review and meta-analysis to evaluate the impact of microlearning compared to macro-learning on the academic performance of students enrolled in higher education. Studies conducted on microlearning in higher education, in which the academic performance in theoretical examinations following microlearning method was evaluated quantitatively and compared with macro-learning. Studies which were reported in English language were included in this review. Ten databases were searched including SCOPUS, EBSCOhost, Emerald, JSTOR, Taylor & Francis, PubMed (MEDLINE), Oxford University Press, ERIC, ACM and IEEE Xplore. The search retrieved 602 studies and 12 studies were included in the systematic review. Cochrane's risk of bias tool was used for the risk of bias assessment of the included studies. Five studies were included in the meta-analysis which was conducted using the RevMan 5.4 software. Meta-analysis showed a higher academic performance in students learned using microlearning (n=344) compared to the students learned using macro-learning (n=310) (p = 0.03). The overall mean difference in academic performance in relation to post-test scores in theoretical examinations between microlearning and macro-learning groups was 12.6 (95% CI: 1.2 - 23.9). Microlearning has contributed to a substantial increase in academic performance among students in higher education compared to macro-learning. Microlearning can increase academic performance of students by reducing cognitive load, providing flexible learning environment, promoting self-directed learning and by providing timely feedback.

Keywords: Andragogy, Higher education, Macro learning, Microlearning

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Introduction

In recent times, higher education has experienced an advancement in the methods of teaching and learning (Sengupta & Blessinger, 2022). Research in higher education is being conducted to explore innovative pedagogies which are suitable for current learners. Microlearning is one such innovative pedagogy which is the process of learning through small-sized, well-planned learning units and short-term learning activities (Allela, 2021; Hug, 2005). Each microlearning unit (i.e. learning object) is designed to achieve a single specific learning objective (Wagner, 2002). The format of the microlearning object can be diverse and depends on the intended learning outcome. Common examples of microlearning objects include short pieces of texts, infographics, PDFs, power point presentations, short videos, eBooks, flipbooks, audiobooks, short podcasts, recorded webinars, short HTML pages, learner-generated blog posts etc. (Allela, 2021).

According to findings of a scoping review on microlearning in higher education, the application of microlearning to higher education has demonstrated many benefits for students, for both objective and subjective outcomes in learning, because microlearning has enhanced motivation to learn and increased confidence in learning (Shatte & Teague, 2020). Moreover, a scoping review on microlearning in health professions education has reported that, microlearning as an educational strategy has revealed a positive effect on the knowledge and confidence of students in health professions education, in studying, retaining knowledge, performing procedures, and engaging in collaborative learning (De Gagne et al., 2019). A scoping review on effects of microlearning has stated that, the positive impact of microlearning on the learner performance is based on the benefits of the shorter, concise, and single-topic content which have been created with a direct relevance to the learning needs of the learners (Taylor & Hung, 2022). Learners can process smaller learning units more easily as those reduce the cognitive load on working memory (Sweller, 1988; Sweller, 2011). Moreover, smaller learning units motivate students to review the content many times, and thereby increase retention (Ebbinghaus, 1964). Furthermore, microlearning has been identified as a well-suited instructional strategy in this digital age because it is suitable for short attention span in the new generation (Allela, 2021).

However, teaching and learning in higher education is still being conducted as a one big piece of information (macro-learning) which is usually 1-2 hour long. Currently, these traditional teaching and learning methods which use macro-learning are being questioned for their effectiveness in this digital age because the attention span of the digital natives has become shorter (Allela, 2021). Therefore, to get a clear understanding of the impact of microlearning compared to macro-learning, it is worthy to quantitatively synthesize evidence of the effect of microlearning compared to macro-learning. Though the effects of microlearning have been qualitatively assessed in previous reviews, to-date there is no quantitative synthesis of the evidence on the effect of microlearning on academic performance of students in higher education. Considering all the above, the objective of this study was to conduct a systematic review and meta-analysis to evaluate the impact of microlearning compared to macro-learning on the academic performance of higher education students. Therefore, the research question (RQ) for the study is as follows.
RQ: Does microlearning significantly improve academic performance of students in higher education compared to macro-learning?

Methodology

The study design for this study is a systematic review and meta-analysis of literature. It was used to summarize the results of selected original research studies.

Criteria for selecting studies for this review

Population

Students in higher education are the population for the review. The definition of higher education, provided by UNESCO was used to identify higher education contexts in the studies. Accordingly, studies which were conducted among students in; "all types of studies, training or training for research at the post-secondary level, provided by universities or other educational establishments that are approved as institutions of higher education by the competent state authorities" (UNESCO, 1998) were included in this review.

Intervention

The intervention is microlearning. Definition for microlearning was used as "the process of learning through small-sized, well-planned modules and short-term learning activities" (Allela, 2021) and we used seven dimensions of microlearning to describe, analyze or generate versions of microlearning; time, content, curriculum, form, process, mediality and learning type were used to identify microlearning interventions (Hug, 2005). The duration of microlearning is ideally two to seven minutes long (Allela, 2021) and not exceeding 15 minutes.

Comparator

Studies that compared microlearning to traditional macro-learning lessons were included in the study. Macro-learning was identified as any comparator the studies have used to deliver teaching and learning which were longer than 15 minutes duration.

Outcomes

The outcome is the academic performance of the students. It was compared in relation to post-test scores in theoretical examinations between microlearning and macro-learning groups.

Design

To ensure this evidence synthesis is based upon the highest quality of evidence, studies which have included a controlled group to compare the impact of microlearning were included and for the meta-analysis the studies which have presented complete outcome data on academic performance of students in theoretical examination were included.

Data collection and analysis

Search strategy

Ten databases were searched for eligible publications including SCOPUS, EBSCOhost, Emerald, JSTOR, Taylor & Francis, PubMed (MEDLINE), Oxford University Press, ERIC, ACM and IEEE

Xplore using the search term as; “microlearning” OR “micro learning” OR “micro-learning” OR “bite-sized learning” OR “just-in-time learning”. The search was conducted from December 2021 to 30th of September2022. No date limitations were placed on the search.

Study selection

Covidence platform was used for the study selection. Research conducted on microlearning in higher education, in which the academic performance in theoretical examinations in the microlearning method was evaluated quantitatively and compared with macro-learning and the studies which were reported in the English language were included in this review.

Two independent investigators conducted the title/abstract screening and full text screening and resolved the conflicts by consensus. The articles considered to be potentially eligible for full text review were retrieved. Full texts were assessed in detail against the inclusion criteria and excluded full texts that did not meet the inclusion criteria and the reasons for exclusion were noted.

Data extraction

For each included study, one reviewer extracted data into a Microsoft Excel data collection form. Data items used during the extraction were as follows; author/s, year of publication, title, country, aim, study design, population, inclusion/exclusion criteria, method of recruitment of participants, baseline population characteristics, field of study, sample size, technology, mode, key features of the course, outcomes of academic performance in relation to post-test scores in theoretical examinations. A second reviewer checked the data for errors and the discrepancies were resolved through discussion and consensus.

Risk of bias assessment

Cochrane’s risk of bias tool (Higgins et al., 2011) was used for risk of bias assessment for the included studies. Risk of bias that rises from the randomization and allocation process, deviations from the planned interventions, missing outcome-level data, measurement of the outcomes, and outcome reporting were assessed in all included studies. Risk of bias was assessed as high, low, or unclear for the five domains: selection, performance, attrition, reporting and other potential threats to validity. Indicating questions within each domain with response options of ‘yes/probably yes’, ‘no/probably no’, and ‘no information’ were used to generate domain-specific judgments of either low risk, some concerns, or high risk of bias. Domain specific risk of bias assessment was used to judge the overall risk of bias for each study. Two reviewers independently conducted the risk of bias assessment and discrepancies were resolved through discussion and consensus.

Measures of treatment effect

Outcome measures of the included studies were all continuous. Therefore, mean-difference was used to summarize estimates of effects from individual studies. The scores of the post-intervention theoretical examination were all entered and directly compared between the microlearning and macro-learning classroom groups as mean differences. The meta-analysis was conducted to generate the unbiased mean effect size, the standard error, 95% confidence interval and values for test of heterogeneity including *Tau*^{2}, *Chi*^{2}, *p* and *I*^{2}. Meta-analysis was conducted using the random effects model.

Data synthesis

Data were synthesized using the random effects model. It was used to generate meta-analytic estimates of effects for each outcome using RevMan 5.4 software, including studies that have presented complete outcome data on academic performance of students in theoretical examination (Han, 2019; Polasek & Javorcik, 2019; Skalka et al., 2021; Wang, 2022; Zhang, 2017). Seven studies were not included in the meta-analysis due to incomplete outcome data. Three of those studies have not mentioned the standard deviations in the mean values (Gao, 2018; Kävrestad & Nohlberg, 2019; Matthews et al., 2014) and four studies have not mentioned the outcome measuring scale (Correa et al., 2018; Leela et al., 2019; Yin et al., 2021; Zarshenas et al., 2022). Out of the five studies which were selected for meta-analysis, two were randomized-controlled trials (RCTs) (Polasek & Javorcik, 2019; Wang, 2022), three were non-randomized studies (NRS) (Han, 2019; Skalka et al., 2021; Zhang, 2017). In Skalka et al (Skalka et al., 2021), results of two studies were presented and those were included in the analyses as Skalka et al, 2021 (1) and Skalka et al, 2021 (2). A subgroup analysis was performed to investigate whether there is significant difference between the results of RCTs and NRS.

Results

Overview

The search retrieved 602 records and among those 50 were duplicates. Out of the 552 studies, 51 studies were selected for full-text review after the title and/or abstract screening. At the end of the full-text review, twelve studies were included in this systematic review and five were included in the meta-analysis. The flow of the studies through the search and selection process is presented in Figure 1.

Figure 1. Flowchart of the article selection for systematic reviews and meta-analyses: The figure shows the databases that were searched, records screened, reasons for excluding the full-texts and the number of studies that were included in the analysis.

Study characteristics

The twelve studies were published from 2014 to 2022 (i.e. number of articles in each year: 2014-1, 2017-1, 2018-2, 2019-4, 2021-2 and 2022-2). The research came from eight countries including, China (*n*=5), Colombia (*n*=1), Czech Republic (*n*=1), Iran (*n*=1), Malaysia (*n*=1), Slovakia (*n*=1), Sweden (*n*=1) and Thailand (*n*=1). The twelve studies under this systematic review included a total of 1177 students in higher education. The included studies are described and summarized narratively in Table 1.

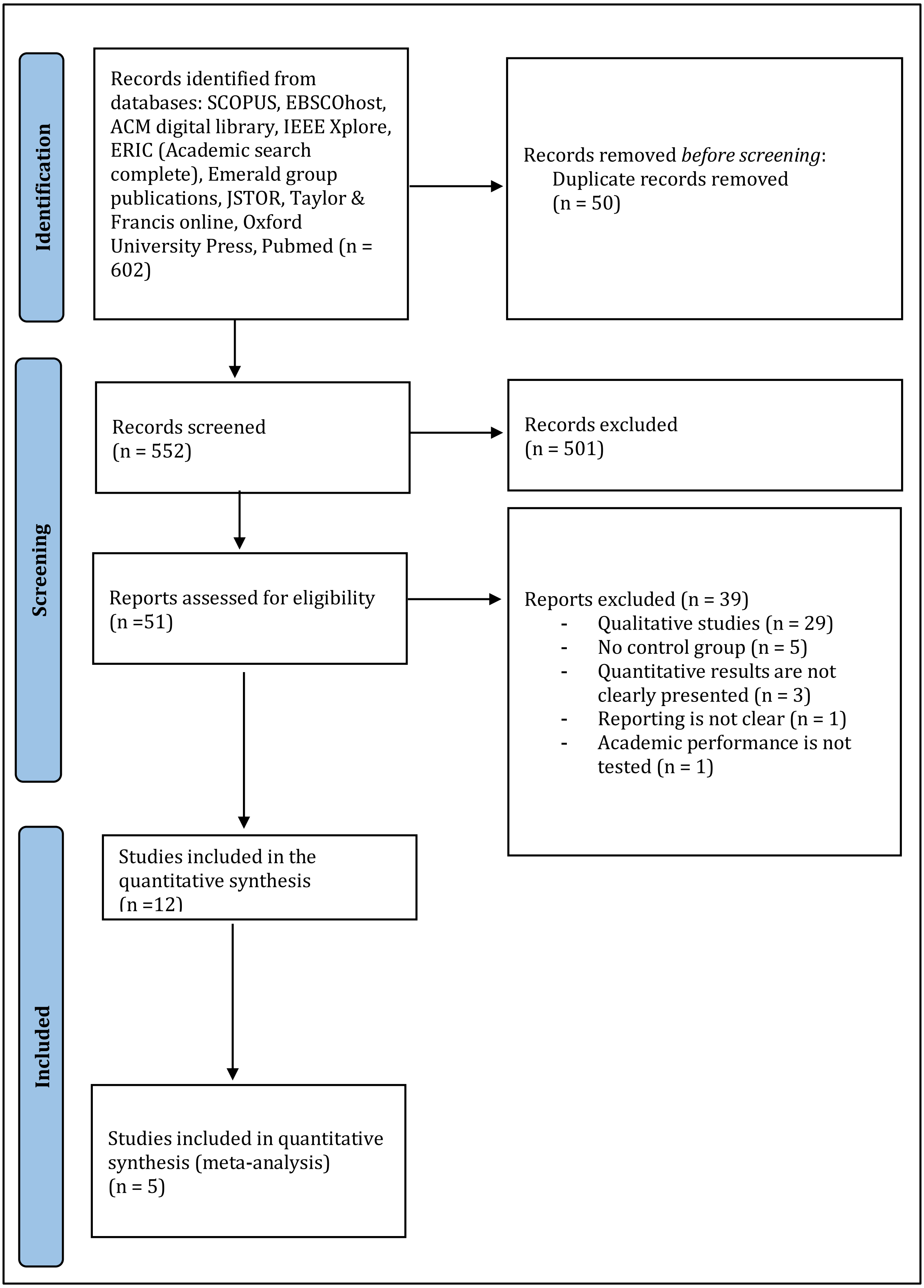

Figure 1: Flowchart of the article selection for systematic reviews and meta-analyses

Table 1: A detailed overview of the included studies

Author, Year, Country, Study design	**Subject of the course/ module**	**Intervention (Mode) , Comparison, Sample size (n)**	**Quantitative outcome measure, Outcome**
(Correa et al., 2018) Colombia Quasi experiment al	Design and construction of software products	Intervention: Group 2- Driving-learning application by only accessing the meso-tasks (follow examples that are designed for each concern; pieces of pre-elaborated code, which are designed based on the concern's descriptions) (online) *n* = 5 Group 3: Driving-learning application by accessing the micro-tasks (follow specific documentation; link to a website, forum, blog, video or a specific explanation text and meso-tasks (online) *n* = 5 Comparison – Group 1: Macro-learning materials (online) *n* = 5	Average of correct answers in questions on content of the course: Average of correct answers (05) is higher in microlearning group (group 3) compared to macro-learning group (03) (group 1). However, there has not been a significant difference of the average of correct answers within the intervention groups and comparison group (Group 2 vs Group 1 – $p = 0.26$, Group 3 vs Group 1- $p = 0.15$).
(Gao, 2018) China Mixed-method	Digital mapping	Intervention: Interactive microlearning course using different types of micro videos (Online) *n* = 57 Comparison: In-class macro-learning *n* = 57	Post-test Theory examination: Microlearning class has achieved better average academic score (86) than the ordinary class (78) Field training: Microlearning class has taken 25 minutes shorter time to accomplish field data acquisition and 20 minutes shorter for software mapping, compared with ordinary class and the mapping accuracy has been 5% higher in microlearning class compared with ordinary class
(Han, 2019) China, Quasi experiment al	English language learning	Intervention: Micro-lecture teaching (Online) *n* = 60 Comparison: Macro-learning (Blended) *n* = 62	Post-test score: The scores of the microlearning group (82.69) have been significantly higher than the scores of the macro-learning group (76.67) ($t = 3.128$, $p = 0.003$, $\alpha = 0.05$)
(Kävrestad & Nohlberg, 2019) Sweden, Mixed method	Routing and Switching Essentials (Data communicatio n)	Intervention: Recorded lectures developed according to the principles of CBMT (Online) *n* = 28 Comparison: Classroom lectures with macro-learning *n* = 23	Average score of theoretical exams and pass/fail of practical exam: The average score is higher in microlearning group (77) compared to macro-learning group (75). There has been no

			statistically significant difference in the mean score and pass/fail rate of students using microlearning and macro-learning.
(Leela et al., 2019) Thailand, Mixed method	Basics of mathematics career: Computational thinking	Intervention: Microlearning using 'living books' (Online) *n* = 52 Control: Classroom Macro-learning *n* = 45	Post-test score The mean score of the microlearning group (16.1) has been significantly higher than the mean score of the macro-learning group (12.62) ($t = 10.37$, $p = 0.00$, $\alpha = 0.01$)
(Matthews et al., 2014) Malaysia, Mixed method	Introduction to C programming	Intervention: Micro-learning objects with duration varied from 5 to 15 minutes (Online) *n* = 50 Comparison: Macro learning objects with duration varied from 20 to 30 minutes (Online) *n* = 51	Post-test score: The mean score of the microlearning group (28.33) has been significantly higher than the mean score of the macro learning group (24.31) in theory examination (t =3.615, $p = 0.00$, $\alpha = 0.05$) Weekly quizzes: The weekly quiz mean score has showed micro-LO group has been performing better than Macro LO group in all the quizzes
(Polasek & Javorcik, 2019) Czech Republic Mixed method	Computer Architecture and Operating System Basics course	Intervention: Microlearning e-learning course with micro-learning units (Online) *n* = 11 Comparison: Macro-learning; e-learning course available to them with material in the form of PDF documents, alongside face-to-face learning *n* = 10	Post-test score The mean score of the microlearning group (19.49) has been significantly higher than the mean score of the macro-learning group (17.52) ($t = 2.187$ $p = 0.045$, $\alpha = 0.05$)
(Skalka et al., 2021), Slovakia, Cohort study	(1) Introductory programming course (2) Advanced programming course	Intervention: Micro-lessons (Online) Advanced: *n* = 36 Introductory: *n* = 87 Comparison: Macro-learning (presentations, video lectures) Advanced: *n* = 37 Introductory: *n* = 51	Post-test score (1) Introductory course: No statistically significant difference between the scores of two groups (2) Advanced course. The mean score of the microlearning group (70.66) has been significantly higher than the mean score of the macro-learning group (46.24) ($p = 0.000026$, $\alpha = 0.05$)
(Wang, 2022), China	English language	Intervention: Micro-video guidance learning (face-to face) *n* = 100	Post-test score The mean score of the microlearning group (52.26) has

Mixed method		Comparison: In-class macro-learning n = 100	been significantly higher than the mean score (43.27) of the macro-learning group (p = 0.027, α = 0.05)
(Yin et al., 2021) China, Quasi experimental	Chatbot-based learning class Education, Tourism Management Macro-learning class: International Economics and Trade, Business Administration	Intervention: Chatbot-based micro-learning system (Online) n = 51 Comparison: In-class macro-learning n = 48	Post-test score The average score of the microlearning group (5.82) is higher compared to macro-learning group (5.75). There has been no significant difference between the learning performance of the two groups (F = 0.02, p = 0.88, α = 0.05)
(Zarshenas et al., 2022) Iran, Quasi experimental	Clinical education in nursing	Intervention: Microlearning content in the form of short videos during the internship through the virtual network in addition to routine training n = 21 Control: Traditional macro-learning methods of lectures and questions and answers n = 25	Post-test score Statistically significant difference in the mean score has been observed on clinical learning level of nursing students between the control (12.4) and experimental groups (14.29) after the intervention (p = 0.041). Also, the difference between the mean score of self-efficacy in the intervention group before and after the training has been statistically significant (p=0.001).
(Zhang, 2017) China, Mixed-method	Civil engineering	Intervention: ARCS+Android mobile micro-lecture teaching platform (Online) n = 50 Comparison: In-class macro-learning n = 50	Post test score: Theory and practical examination. The mean score of the microlearning group (97.34) has been significantly higher than the mean score of the macro-learning group (67.72) in theory examination (t =2.45 , p = 0.001, α = 0.05) The mean score of the microlearning group (90.21) has been significantly higher than the mean score of the macro-learning group (60.51) in the practical examination (t = 3.57, p = 0.003, α = 0.05)

Description of interventions

All the included studies compared microlearning to macro-learning. In eleven studies, microlearning courses were delivered in the online mode (Correa et al., 2018; Gao, 2018; Han, 2019; Kävrestad & Nohlberg, 2019; Leela et al., 2019; Matthews et al., 2014; Polasek & Javorcik, 2019; Skalka et al., 2021; Yin et al., 2021; Zarshenas et al., 2022; Zhang, 2017). Ten of those studies have used micro-videos as the format of the microlearning objects while one study (Correa et al.,

2018) has used short pieces of texts, blogs, web-links as microlearning objects. In one study (Wang, 2022), microlearning course has been delivered in the face-to-face mode in which micro-videos have been shown to students as the learning material in the classroom. In seven studies, macro-learning courses have been delivered as traditional classroom lectures (Gao, 2018; Kävrestad & Nohlberg, 2019; Leela et al., 2019; Wang, 2022; Yin et al., 2021; Zarshenas et al., 2022; Zhang, 2017). In three studies, macro-learning courses have been delivered in the online mode (Correa et al., 2018; Matthews et al., 2014; Polasek & Javorcik, 2019) as online lectures and in two studies, blended learning mode has been used to deliver macro-learning courses, which used in-class lectures and online lectures and videos to deliver the content (Han, 2019; Skalka et al., 2021).

Risk of bias assessment

The three RCTs had a low risk of bias in the domain of selection bias. In four studies, the domain of selection was described poorly. Therefore, the domain of selection was assessed as unclear for those four studies. The NRS had a high risk of selection bias. It was not possible to blind the students to the learning design interventions. Therefore, the domain of performance bias was assessed as unclear. Detection bias was inadequately described in the studies, and therefore the risk was unclear. Six studies were determined high risk for attrition bias due to incomplete outcome data. In three of those, standard deviation values were not mentioned and in the other three studies the outcome measuring scale was not mentioned. Reporting bias was assessed as low for all studies. The risk of bias summary and the risk of bias graph is shown in Figures 2 and 3.

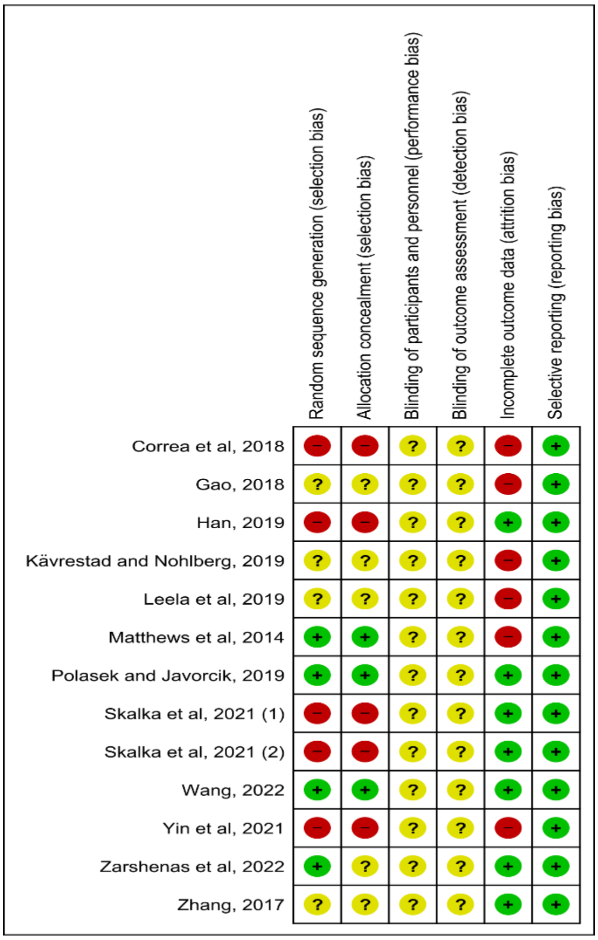

Figure 2: Risk of bias summary

Figure 2. Risk of bias summary: This figure shows review authors' judgments about each risk of bias item for each study included in the review. The domains for risk of bias are selection bias, performance bias, detection bias, attrition bias and reporting bias.

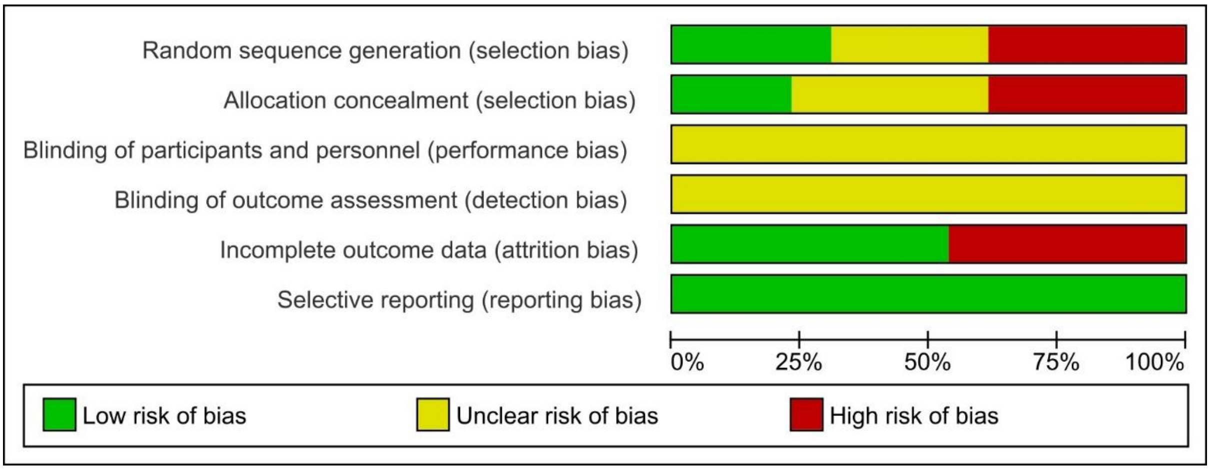

Figure 3: Risk of bias graph

Figure 3. Risk of bias graph: This figure shows review authors' judgments about each risk of bias presented as percentages across all included studies in the systematic review.

Impact of microlearning on academic performance

All the twelve studies included in the systematic review have reported increased academic performance in students who were in the microlearning group compared to the students in the macro-learning group. This was observed in the performance of students at theoretical examinations in all twelve studies. A meta-analysis was conducted including the studies that have presented complete outcome data on academic performance of students in theoretical examinations (Han, 2019; Polasek & Javorcik, 2019; Skalka et al., 2021; Wang, 2022; Zhang, 2017).

Heterogeneity assessment

Meta-analysis of the academic performance in relation to post-test scores in theory examination showed high heterogeneity (Tau^2 = 189.3, Chi^2 = 242.65, I^2 = 98%, df = 6, p < 0.00001). There were two RCTs and three NRS in the meta-analysis for a total of 654 students. The subgroup analysis between the study types, RCTs versus NRS, showed no difference in academic performance between the results of RCTs and NRS (p = 0.45). Therefore, all the five studies were considered together.

Meta-analysis

Meta-analysis showed a higher academic performance in students learned using microlearning compared to the students learned using macro-learning (p = 0.03). The overall mean difference in academic performance in relation to post-test scores in theoretical examinations between microlearning and macro-learning groups was 12.6 (95% *CI*: 1.2 - 23.9) (Figure 4).

Study or Subgroup	Microlearning Mean	SD	Total	Macro-learning Mean	SD	Total	Weight	Mean Difference IV, Random, 95% CI
Han, 2019	82.69	7.32	60	76.67	9.55	62	17.4%	6.02 [3.01, 9.03]
Polasek and Javorcik, 2019	69.61	9.43	11	62.57	4.64	10	16.7%	7.04 [0.77, 13.31]
Skalka et al, 2021 (1)	46.24	33.91	87	47.6	27.46	51	15.4%	-1.36 [-11.73, 9.01]
Skalka et al, 2021 (2)	70.66	22.6	36	46.24	20.96	37	15.5%	24.42 [14.41, 34.43]
Wang, 2022	52.26	10.56	100	43.27	13.02	100	17.4%	8.99 [5.70, 12.28]
Zhang, 2017	97.34	6.54	50	67.72	3.22	50	17.5%	29.62 [27.60, 31.64]
Total (95% CI)			**344**			**310**	**100.0%**	**12.57 [1.24, 23.90]**

Heterogeneity: Tau² = 189.30; Chi² = 242.65, df = 5 (P < 0.00001); I² = 98%
Test for overall effect: Z = 2.17 (P = 0.03)

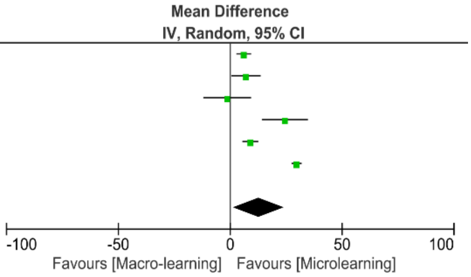

Figure 4: Forest Plot of Comparison

Figure 4. Forest Plot of Comparison: This figure shows the effect of microlearning on academic performance compared to macro-learning.

Discussion

Adopting microlearning in higher education had resulted in an increase in academic performance compared to macro-learning. According to the meta-analysis, post-test scores between microlearning and macro-learning showed a mean difference of twelve marks, highlighting microlearning can contribute to a substantial increase in academic performance in students. The higher academic performance through micolearning has been achieved by positive effects of microlearning such as; ability to learn through short and concise learning content (Han, 2019; Matthews et al., 2014; Yin et al., 2021; Zarshenas et al., 2022), providing flexible learning environment (Han, 2019; Yin et al., 2021; Zarshenas et al., 2022), receiving timely feedback through interactions with teachers (Han, 2019; Yin et al., 2021), opportunity to repeat learning content, any number of times until students feel that they have achieved the learning objective (Han, 2019; Yin et al., 2021; Polasek & Javorcik, 2019) and engaging in self-directed learning (Han, 2019; Yin et al., 2021). Moreover, perceptions of the students revealed that, microlearning has resulted in high satisfaction (Correa et al., 2018; Leela et al., 2019), positive attitudes towards the course (Matthews et al., 2014; Polasek & Javorcik, 2019; Zhang, 2017), increased interest (Gao, 2018; Yin et al., 2021; Wang, 2022), and improved learning motivation (Han, 2019; Kävrestad & Nohlberg, 2019; Yin et al., 2021).

Cognitive load theory explains that the capacity of the human brain to process information is limited (Sweller, 1988; Sweller, 2011). The human brain tends to retain more information when the content is structured in small pieces (Allela, 2021). Therefore, in instructional design, presenting learning content as interacting but isolated elements can decrease cognitive load (Sweller, 2011) and thereby can increase retention. In contrast, when learning content is delivered to students as one big piece of information, which happens in macro-learning, student's brain must process a high cognitive load at once (Yin et al., 2021), which will lead to low information retention. Therefore, short, and concise learning content which aims to fulfill single learning objective, in microlearning might have contributed to higher academic performance in students who followed microlearning courses compared to traditional courses, through reducing the cognitive load.

According to Ebbinghaus's forgetting curve, memory (retention in learning) weaken over time and the biggest drop of retention occurs soon after learning. By repetitively reviewing what we learn, we can reduce the rate at which we forget by halting the forgetting curve (Ebbinghaus, 1964). The small and concise content in microlearning courses has facilitated the students to go through the content, watch and replay the micro-videos any number of times they needed. This repetition might have contributed to increased academic performance in students in microlearning, compared to students in macro-learning, who had only one opportunity to learn the content in the traditional classroom.

Short and segmented content in microlearning courses have provided the students with a flexible learning environment, as they can go over only the part that is unclear to them without having to go over the long lessons all over again. The students could go through the exact micro-content they want to revisit to achieve the learning objective. This flexibility might have motivated the students to learn, which in turn facilitates their academic performance. In a macro-learning environment, the students must attend the classes physically, in a scheduled time and the teacher controls the pace of teaching. As it is not possible to accommodate the learning needs of every student it can lead to decrease in motivation to learn and thereby decrease academic performance (Yin et al., 2021).

Students in higher education are adult learners. The andragogical model of learning presented by Malcolm Knowles, explains that the adult learners have a "self-concept" of being responsible for their own decisions, for their own lives and therefore on their own learning. Therefore, they have a need to be seen and treated by others as being capable of self-direction (Knowles et al., 2005). In microlearning courses in the included studies, students were required to go through the learning content by themselves and answer questions at the end of content. This promotes self-directed learning and goes along with how they learn as adults. In traditional macro-learning, the teacher has delivered the content while students listen. This makes the students become passive consumers of information, which is not compatible with how they learn as adults. Moreover, adult learners are assumed to dislike and resist situations in which they feel others are forcing their ideas on them (Knowles et al., 2005). Therefore, the promotion of self-directed learning in microlearning might have contributed to the increased academic performance in students who followed microlearning courses, by making the learning process compatible with how they learn as adults.

In the included studies, at the end of each micro-content students were required to answer a set of questions to make sure that they have achieved the learning objectives. As soon as they answered the questions, they were given feedback. Timely feedback is considered crucial for the success of learning because it connects the individual learners to teachers (Jensen et al., 2021) and increases interactivity between teachers and students in education (Barboza & da Silva, 2016). Through timely feedback in microlearning courses students have got the opportunity to make sure they have achieved the learning objective for that content and that they could move onto other content. Therefore, the students gradually master the interrelated concepts and then they learn to integrate those to achieve the major learning outcome of the course (Matthews et al., 2014) which might have positively contributed to their academic performance.

Accordingly, the above attributes of microlearning have facilitated the increased academic performance of students who followed microlearning courses, compared to traditional learners. Further to these attributes, microlearning has been mentioned to be suitable for short attention span of the current learners (maximum 20 minutes) which is diminishing more (Allela, 2021). However, few factors have been identified that can mitigate the effectiveness of microlearning in instructional design. Those are, lack of motivation of the learner for self-learning, content fragmentation where students may fail to draw connections between the different fragments of learning contents to see the overall picture (Allela, 2021) and technology barriers as poor internet connection or unavailability of technological device (Allela, 2021; De Gagne et al., 2019). Therefore, to effectively achieve positive attributes of microlearning in higher education, teachers should consider the learning needs of their students as adult learners and design microlearning content that are of the appropriate size for cognitive processing, linked to relevant learning objectives, and to be accessible through multiple devices and platforms (Major & Calandrino, 2018).

Our study has several strengths and limitations. To the best of our knowledge, the present study is the only systematic review and meta-analysis on the effect of microlearning on academic performance in higher education students, compared to macro-learning. Present systematic review has revealed important attributes of microlearning which can improve academic performance in students. This meta-analysis provides a quantitative synthesis of the effect of microlearning on academic performance in relation to post-test scores in theory examination, compared to macro-learning. However, only two of the included studies have used randomization during participants' allocation which has resulted in high risk of selection bias. Therefore, interventional studies conducted with more rigor and thereby less bias are required to draw more solid conclusions. Literature providing quantitative evidence on the effect of microlearning in practical performance is scarce. Four studies in this systematic review have reported findings on practical performance (Gao, 2018; Kävrestad & Nohlberg, 2019; Zarshenas et al., 2022; Zhang, 2017) and only one of those studies has reported complete outcome data regarding practical performance (Zhang, 2017). Therefore, a meta-analysis could not be conducted on the effect of microlearning on practical performance of higher education students. Our study was limited to publications in English language. Therefore, findings of research which were reported in other languages are not included in this study. Despite these limitations, the result is likely to represent the effect of microlearning on improving academic performance in students in higher education, when compared to macro-learning.

Conclusion

Meta-analysis showed higher academic performance in students who learned using microlearning (n = 344) compared to the students who learned using macro-learning (n = 310) (p = 0.03). The overall mean difference in post-test scores in theoretical examinations between microlearning and macro-learning groups was 12.6 (95%CI: 1.24 - 23.9). This mean difference of scores highlights that microlearning can contribute to a substantial increase in academic performance in students compared to macro-learning. Microlearning can increase academic performance of students by reducing cognitive load, providing flexible learning environment, promoting self-directed learning and by providing timely feedback. Designing microlearning lessons according to the adult learning principles can further enhance the positive impact of microlearning on the academic performance of students in higher education.

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