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Abstract. Previous research into confusion and learning neglects to investigate how this relationship varies when faced with impact factors such as multiple types of affect and learning measurements, learning environment, or grade level. Moreover, past research also reports diverse effect size values for this relationship, making the correlation ambiguous. As such, the current research seeks to reconcile these nuances between confusion and learning through a meta-analytic approach. In this analysis, it was found that there was no relationship between confusion and learning gains, or in the subgroup analysis of grade level. Since only one impact factor, grade level, was analyzed, it is considered that the analysis of other or multiple impact factors could help to further understand the association between confusion and learning. It is also reasoned that variability in the definitions of confusion and learning in the papers included in the meta-analysis as well as publication bias contribute to this result. As such, future research may choose to investigate these avenues and continued research generally into the association between confusion and learning would also be helpful to better understand this relationship.

Keywords: Confusion, Learning, Affect.

1 Introduction

Confusion is an epistemic emotion that arises due to an incongruity between novel incoming information and existing knowledge during cognition processing [1, 2]. This state is also commonly referred to as cognitive disequilibrium, where an individual might experience an impasse, goal disruption, inconsistencies, aberrations, and cognitive dissonance [1]. As such, confusion plays a critical role in learning as this affective state is involved in problem solving, communicating reappraisal, and motivating behavior [1, 3]. Most literature posits that this affective state can thus be beneficial for learning because the ability to resolve cognitive disequilibrium leads to a deeper understanding of learned material [1, 4]. Nevertheless, if this experienced impasse during confusion is not properly resolved, confusion can be harmful to learning [4, 5] and confusion alone can have a negative impact on student achievement [6].

While confusion appears to be beneficial to learning if properly induced and then resolved, there are inconsistencies in this past research that inhibit the verification of this described relationship between confusion and learning. For instance, many inquiries into confusion and learning study experiences from online tutoring or educational software, neglecting to view how such results may differ in live in-person situations [7, 8]. Additionally, it is unclear how this relationship might be affected by impact factors like types of affect and learning measurements, learning environment, or grade level. For instance, previous research into the relationship between confusion and learning utilize various means of affect measurement such as self-report means, autonomous mechanisms, and professional judgements, all of which are known manners to measure an affective state [9]. The other impact factors are varied in this respect as well in most previous literature.

Analogous to the variability in impact factors, the prior documented correlation between confusion and learning gains is also contrasted, evidenced by effect size values that range from -0.007 to 0.547 [10, 11]. Such diversity makes it difficult to completely classify the relationship between confusion and learning. It is for this reason that the present meta-analysis takes place as the motivation for the current study is to determine the overall correlation between confusion and learning. Due to the apparent diversity in recorded effect sizes, as well as acknowledging the possible factors impacting this relationship, it is expected that there will be a negative relationship or no relationship between confusion and learning.

2 Method

2.1 Literature Search

Searches were conducted from April to August of 2021 using databases Google Scholar and ERIC. The search utilized the phrases *confusion*, *learning AND confusion, learning AND affect,* and *learning AND confusion OR affect* to investigate how confusion relates to learning. Results from these searches were first limited to articles that mentioned the relationship between confusion and learning in the abstract and results section. Additionally, the search was further refined by articles that reported Pearson's correlation coefficients for this relationship or a convertible. The initial search identified 70 articles ignoring duplicate records, but a total of 9 articles were identified to include all selection criteria. Most of the articles were removed due to not providing the statistical values necessary for the meta-analysis.

2.2 Coding Procedure

Information cataloged from each article included (a) type of learning environment, (b) grade level, (c) type of affect measurement, (d) type of learning measurement, and (e) Pearson's correlation coefficient or convertible value. The learning environment was categorized as in-person, educational software or online tutoring/ class, or a video game. The grade level was differentiated into either university students or middle school students while the types of affect measurement were categorized as self-report, retrospective judgement, professional coding, or automatic detection through technological interface. Lastly, the types of learning measurements were categorized as either a scaffolding model or a comprehension test. The characterized information in (a) through (d) acted as the apparent impact factors mentioned in the introduction. Of the catalogued information, only impact factors with variable samples are considered.

2.3 Meta-Analytic Procedure

To account for various experimental designs and methods of measurements of confusion and learning outcomes, analyses were done using every relevant sample that was reported within each publication to account for variation across all methods and samples [12]. Therefore, each sample used in the meta-analysis represents an independent group of participants removing the between- and within-subjects design distinction. From the nine studies, 11 samples were obtained. To be included in the analysis, studies were required to report a Pearson's product-moment correlation or statistical values that could be used to approximate a Pearson's correlation. To account for multiple measures from the same sample, a multilevel meta-analysis was performed.

The meta-analysis was conducted using the *metafor* package [13, 14]. To examine the relationship between confusion and learning outcomes, a 3-level, mixed-effects model was performed with correlation measurement (Level 3) nested under sample (Level 2). To assess differences between class level, "pairwise comparisons" were performed by using the mixed-effects model structure with either class level as a moderating variable.

3 Results

Table 1 displays the studies used in the meta-analysis. Due to needed variability in subgroup samples, grade level is the only impact factor analyzed.

Table 1. Summary of studies included in the meta-analysis.

Authors	**Year**	**Sample**	**Grade**	***r***	***n***
D'Mello & Graesser	2014	1	U	-0.148	88
D'Mello & Graesser	2014	1	U	-0.05	88
Graesser et al.	2007	2	U	0.49	30
Gong et al.	2019	3	U	0.547	30
Bradbury et al.	2017	4	U	0.39	32
Bosch & D'Mello	2013	5	U	-0.274	27
Bosch & D'Mello	2013	5	U	0.256	27
Bosch & D'Mello	2013	5	U	0.046	20
Bosch & D'Mello	2013	5	U	-0.094	20
San Pedro et al.	2015	6	M	-0.16	1376
San Pedro et al.	2015	6	M	0.076	1376
Pardos et al.	2014	7	M	-0.16538	629
Pardos et al.	2014	7	M	-0.08912	629
Pardos et al.	2014	8	M	0.3737	764
Pardos et al.	2014	8	M	0.23457	764
Bosch & D'Mello	2015	9	U	0.087	99
Bosch & D'Mello	2015	9	U	0.058	99
Bosch & D'Mello	2015	9	U	-0.007	99
Rodrigo et al.	2010	10	M	-0.256	58
Rodrigo et al.	2010	11	M	-0.108	69

Note. U = University Students, M = Middle School Students.

Analyses were first completed at the overall level and then at the subgroup level. Eleven samples with 20 measurements were utilized in the overall analysis. Tests of homogeneity demonstrated that the samples came from a heterogenous distribution, $Q = 290.70$, $p < .001$. Table 2 portrays this overall relationship between confusion and learning gains as well as the subgroup measurements. There was no overall relationship between confusion and learning found, $\beta = .084$, $SE = 0.08$, $p = .285$.

Of the 11 total samples, six samples with 12 measurements assessed university students and five samples with eight measurements assessed the middle school students. Both subgroups came from heterogenous distributions, $Q = 36.53$, $p < .001$ and $Q = 252.66$, $p < .001$, for university and middle school students respectively. There was no difference between grade levels in the relationship between confusion and learning, $\beta = 0.22$, $SE = 0.15$, $p = .160$.

Table 2. Summary of the relationship between confusion and learning outcomes.

	Samples k	**Participants N**	**β**	***SE***	***p***
Overall	11	6324	0.084	0.08	0.285
Grade Level					
University Students	6	659	0.205	0.11	0.102
Middle School Students	5	5665	-0.027	0.1	0.798

4 Discussion

The present meta-analysis offers descriptive insight into the relationship between confusion and learning outcomes. Overall, there was no relationship found between confusion and learning, as predicted. This result is different than past research that usually views a positive correlation between confusion and learning [4, 15, 16]. This difference might be attributed to the variability in the papers included in the meta-analysis which exhibit a wide range of effect sizes concerning this relationship as discussed above. Moreover, despite there being no difference between grade levels in the relationship between confusion and learning, a comprehensive view involving various impact factors might still be possible. This study was limited, and only grade level was analyzed. It is plausible that other impact factors such as affect and learning measurements, learning environment, or a larger sample for grade levels could contribute to this understanding. More impact factors could also be considered like number of participants or the length of the study. Correspondingly, it is for this reason concerning impact factors that some researchers argue for reform in educational research and data collection. For instance, arguments have been made for multimodal learning analytics that are more inclusive for studying learning and not only easy to collect by researchers [17]. As such, it is conceivable that past research concerning this association did not uncover the full relationship between confusion and learning because only single types of measurements were collected, most of which are akin to types of measurements made previously. Future research may consider varied or multiple types of impact factors to explore the relationship between confusion and learning outcomes more fully.

The definitions used for both confusion and learning gains in all papers utilized in this meta-analysis were also diverse. For example, some of the included papers in the meta-analysis view confusion as a singular event [7, 11, 18–21] while the others describe confusion in terms of a transition state [6, 10, 22]. This variation in how confusion is understood might aid in explaining the result of this study and the wide range of effect sizes viewed prior. Defining confusion as a single point in time and as one affective state versus in transition with other affective emotions opens more avenues of research and calls for a more definitive definition of confusion. Likewise, the definition of learning is also contrasted in the papers included in the meta-analysis. As mentioned in the methods, learning can be categorized and coded for various learning measurements such as comprehension testing and a scaffolding model. This varied understanding of learning may have also contributed to the result.

Lastly, this result could also be a consequence of publication bias. It is possible that the pioneering articles detailing the positive and beneficial relationship between confusion and learning prompted conjecture of this correlation and led current research in this direction [4, 15, 16]. Furthermore, by cementing this relationship in the literature, many follow-up studies now tend to assess only the detection of confusion in the learning process instead of learning gains due to the belief in the positive correlation between confusion and learning. It is the hope of researchers that with this proposed understanding, detection of confusion in online tutoring or learning can help students learn better online [23]. Accordingly, this bias impedes current research and may help explain the present result.

In conclusion, due to the varied effect sizes in current research surrounding confusion and learning, as well as the effect of impact factors on this relationship, this research sought to assess this association with a meta-analytic approach. As predicted, there was no relationship between confusion and learning gains. Despite belief that impact factors might affect this relationship, the subgroup analysis of grade level was not significant. Nevertheless, this study was limited in the small amount of pooled data in the analysis, with only nine papers found to match the search criteria. It is also limited by the variation in impact factors, even if all were not able to be analyzed, and the diverse definitions used for both confusion and learning gains in all the papers included in the meta-analysis. Publication bias is also reasoned as a factor in these results. Considering these limitations, future research may still choose to assess the relationship between confusion and learning by taking various or multiple types of impact factors into account. Additionally, more research that investigates confusion in terms of learning gains, and more concrete definitions of both, would be helpful to draw further conclusions regarding this relationship.

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