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Meta-Analysis on The Effectiveness of Personalized Recommendation Systems Using Inclusion and Exclusion Criteria

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Abstract- ***This paper conducted a meta-analysis on the effectiveness of personalized recommendation systems using Inclusion and exclusion criteria. Dataset extraction was based on preferred reporting items for systematic reviews and meta-analyses through literature search and article selection. The meta-analysis was based on nine studies consisting of a total of 268,132 observations. The effect size was measured using standardized difference mean which was determined through a Google search. The random-effects model was employed for the analysis. The studies in the analysis were assumed to be a random sample from a universe of maternal mortality studies in Nigeria. The mean effect size was 1.566 with a 95% confidence interval of 1.194 to 2.053. The Z-value tested the null hypothesis that the mean effect size is 1. We found $Z = 3.244$ with $p < 0.001$ for $\alpha = 0.05$; hence, we rejected the null hypothesis and concluded that the mean effect size was not precisely 1 for personalized recommendation systems. The Q-statistic provided a test of the null hypothesis that nine studies in the analysis share a common effect size; the Q-value is 15.97 with 8 degrees of freedom (k-1) and $p < 0.001$. For $\alpha = 0.1$, we rejected the null hypothesis that the true effect size was the same in all the 9 studies since Q=k-1, k being the number of studies. The I-squared statistic was 65.3%, which tells us that some 65.3% of the variance in observed effects reflected variance in true effects rather than sampling error. Tau-squared, the variance of true effect sizes, was 0.114 in log units. The study recommended that there should be personalized controlled plans, this will help optimize outcomes and reduce the occurrence of severe mean effects.***

Indexed Terms- Meta-analysis; Inclusion and Exclusion Criteria; Effect Size; I2 statistic; Q-test.

I. INTRODUCTION

Recommendation system is a contemporary issue and will attract the attention of many and since meta-analysis is facing misconception or misconstrained to be useful only in bio-data, this kind of topic will correct the notion. (Adehi & David, 2024). Furthermore, am moved to research on this area because there are as been low evidence on the effectiveness of personalized recommendation systems that is used online platforms such as Netflix or Amazon. Also, there are lots of evidences of effort by researchers in some part of the world to determine the effectiveness of recommendation systems, many of these researchers' report has conflicting results in the magnitude to the subject matters. Due to the data summarized may not be the same, grouping different recommenders may lead to meaningless estimates of effect in research reports. Categorically, these controversies looming our society. Nowadays, recommender systems are being increasingly used for a large number of applications such as web (Castellano *et al*., 2011), books (Crespo *et al*., 2011), e-learning (Salehi *et al*., 2012), tourism (Lorenzi *et al*., 2011), movies (Bobadilla *et al*., 2010), music (Yoshii *et al*., 2008), e-commerce, news, specialized research resources (Porcel *et al*., 2009), television programs (Shin *et al*., 2009), etc. It is therefore important to build high-quality and exclusive recommender systems for providing personalized recommendations to the users in various applications. Despite the various advances in recommender systems, the present generation of recommender systems requires further improvements to provide more efficient recommendations applicable to a broader range of applications. More investigation of the existing latest works on recommender systems is required which focus on diverse applications. There is hardly any review paper that has categorically synthesized and reviewed the literature of all the classification fields and application domains of recommender systems. The few existing literature reviews in the field cover just a fraction of the articles or focus only on selected aspects such as system evaluation. Thus, they do not provide an overview of the application field, algorithmic categorization, or identify the most promising approaches. Also, review papers often neglect to analyze the dataset description and the simulation platforms used.

The aim of this paper is to evaluate the effectiveness of personalized recommendation systems that is used in online platforms. The objectives are follows

1. To use difference in mean to analysis user behavior for personalized recommendation systems using meta-analysis.
2. To assess the accuracy of recommendations and variation (heterogeneity) among published data using Q test and I square statistics.

This aims to fulfill this significant gap by reviewing and comparing existing articles on recommender systems based on a defined classification framework, their applications focused, their features and challenges, dataset description and system performance. Finally, to provide researchers and practitioners with insight into the most promising directions for further investigation in the field of recommender systems under various applications. In essence, recommender systems deal with two entities users and items, where each user gives a rating (or preference value) to an item (or product). User ratings are generally collected by using implicit or explicit methods. Implicit ratings are collected indirectly from the user through the user's interaction with the items. Explicit ratings, on the other hand, are given directly by the user by picking a value on some finite scale of points or labeled interval values. For example, a website may obtain implicit ratings for different items based on clickstream data or from the amount of time a user spends on a webpage and so on. Most recommender systems gather user ratings through both explicit and implicit methods. Researchers have long been aware of the need for organizing this vast literature so that it will be more useful to policy makers, administrators, teachers, and other researchers (Massdex *et al*, 2001).

A recommendation system is a system or application that helps the user to select a suitable item or finding relevant information among a set of candidates using a knowledge-base that can either be hand coded by experts or learned from behaviors of the users. Typically, a recommendation system performs three of functions (Olsson, 2003). The use of meta-analysis (MA) in information systems (IS) research has gained considerable traction over the last couple of decades. As the IS discipline continues to mature and grapple with various applications of information technology (IT) for individuals, organizations, and societies, there has been an increasing need to synthesize extant research, reconcile inconsistent empirical findings, identify gaps in knowledge, and chart paths for future research (e.g., King & He, 2005). MA serves as a powerful alternative or supplement to traditional literature reviews for research synthesis in the IS discipline, possibly in the context of systematic reviews[1] as well. MA studies in IS have tackled a variety of research questions dealing with behaviors of individuals, organizations, and teams (Clement, & Williams, 2019). MA studies in IS thus strive to go beyond the traditional MA goals of reconciling inconsistent findings, resolving the magnitudes and directions of the relationships, and identifying moderators that may alter the effects between variables Sabherwal et al., (2006).

II. RESEARCH METHODOLOGY

Research Design

In this paper, the method of analysis used in this research work is literature search and articles selection using inclusion and exclusion criteria. A search procedure was executed to find results of empirical studies on personalized recommendation systems.

Data Extraction and Quality Assessment

For each study, the following data were extracted: author's name; publication year; country in which the study was performed; study design; source of recommender system (in content-based recommender systems); online users - sample size; effect size (mean difference); type of outcome (accuracy and effectiveness).

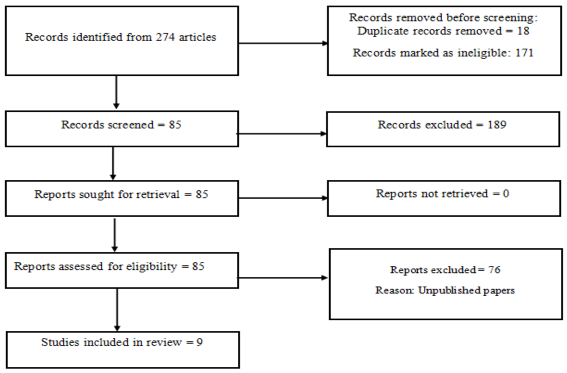


Figure 1: Flowchart diagram showing the inclusion and exclusion process.

Model Specification

The theoretical frame work of this study is based on the assumptions of meta-analysis models. There are fixed and random effect model. (Borenstein et al., 2011)

$$Y_1 = \begin{cases} \vartheta + E_i & fixed\ effect \\ \mu + \vartheta_i + e_i & random\ effect \end{cases}$$

where

E_i and $e_i \sim N(0, \sigma^2)$, where i = 1,2,..,k

Ei is the sampling error

e_i is the random deviations of study's observed effect from the true effect size

ϑ is the population mean

ϑ_i is the true effect size (mean difference)

μ is the grand mean

In a fixed effect analysis, we assume that all the included studies share a common effect size, μ. The observed effects will be distributed about μ, with a variance σ^2 that depends primarily on the sample size for each study.

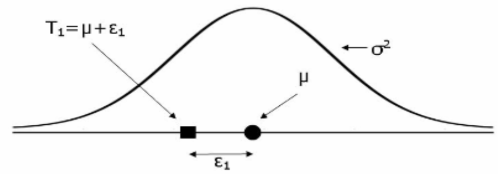


Figure 2: The fixed effect model for the weighted average (Weiss & Daikeler, 2017)

Generally, for any observed effect T_1,

$T_1 = \mu + \varepsilon_1$
(3.0)

Assigning weights to the studies

In the fixed effect model, there is only one level of sampling, since all studies are sampled from a population with effect size μ. Therefore, we are dealing with only one source of sampling error-within studies (e).

$$w_i = \frac{1}{\phi_i} \qquad (3.1)$$

Where ϕ_i is the within-study variance for study (i).

The weighted mean ($\overline{T}_.$) is then computed as

$$\overline{T_.} = \frac{\Sigma_{I=1}^{K} W_i T_i}{\Sigma_{i=1}^{k} w_i} \qquad (3.2)$$

That is, the sum of the products $W_i T_i$ (effect size multiply by weight) divided by the sum of the weights.

The variance of the combined effect is defined as the reciprocal of the sum of the weights

$$V_. = \frac{1}{\Sigma_{i=1}^{k} W_i} \qquad (3.3)$$

And the standard error of the combined effect is then the square root of the variance

$$SE(\overline{T}_.) = \sqrt{V_.} \qquad (3.4)$$

The 95% confidence interval will be computed by

$$\text{Lower Limit} = \overline{T}_. - 1.96 * SE(\overline{T}_.) \qquad (3.5)$$

$$\text{Upper Limit} = \overline{T}_. + 1.96 * SE(\overline{T}_.) \qquad (3.6)$$

For the Z value

$$Z = \frac{\bar{T}_{.}}{SE\,(\bar{T}_{.})} \qquad (3.7)$$

For a one tailed test p-value is

$$P = 1 - \phi(Z) \qquad (3.8)$$

and for a two tailed test by

$$p = 2[1-\phi|z|] \qquad (3.9)$$

Where $\phi(z)$ is the standard normal cumulative distribution function.

Random Effect Model

Random effect also called variance component model, is a statistical model where the model parameters are random variables. It is a kind of hierarchical linear model, which assumes that the data being analyzed are drawn from a hierarchy of different populations whose differences relate to that hierarchy.

and computed the variance of these effects sizes (across an infinite number of studies), this variance would be τ^2.

For a set of S effect size measure (γ)

$$\hat{\gamma}_R = \frac{\sum_{i=1}^{S} w_i \hat{\gamma}_i}{\sum_{i=i}^{S} w_i} \qquad (3.10)$$

$$W^* = \frac{1}{S^2(\hat{\gamma}_i)+\tau^2} \qquad (3.11)$$

$$\tau^2 = \frac{Q-(S-1)}{\sum_{i=i}^{S} w_i - \frac{\sum_{i=i}^{S} w^2{}_i}{\sum_{i=i}^{S} w_i}} \quad \text{for } Q > S-1 \qquad (3.12)$$

One method for estimating τ^2 is the method of moments (or the DerSimonian and Laird) method, as follows.

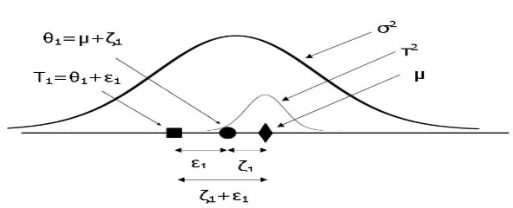


Figure 3: The random effect model for the weighted average (Viechtbauer et al., 2007)

Generally, for any observed effect T_i,

$$T_i = \theta_i + e_i = \mu + \zeta_1 + e_i \qquad (3.13)$$

Assigning weights under the random effects model

In the fixed effect analysis, each study was weighted by the inverse of its variance. In the random effects analysis to each study will be weighted by the inverse of its variance. The difference is that the variance now includes the original (within-studies) variance plus the between-studies variance, tau-squared.

Note the asterisk sign (*) will be used to represent random effect

$$w_i^* = \frac{1}{\phi_i^*} \qquad (3.14)$$

Where ϕ_i^* is the within-study variance for study (i) plus the between-studies variance, tau- squared. That is

$$v_i^* = v_i + \tau^2 \qquad (3.15)$$

The weighted mean ($\bar{T}_{.}^{*}$) is then computed as

$$\bar{T}_{.}^{*} = \frac{\sum_{i=1}^{k} w_i^* T_i}{\sum_{i=1}^{k} w_i^*} \qquad (3.16)$$

That is, the sum of the products divided by the sum of the weights.

The variance of the combined effect is defined as the reciprocal of the sum of the weights, or

$$v_{.}^{*} = \frac{1}{\sum_{i=1}^{k} w_i^*} \qquad (3.17)$$

And the standard error of the combined effect is then the square root of the variance,

$$SE(\bar{T}_{.}^{*}) = \sqrt{V_{.}^{*}} \qquad (3.18)$$

The 95% confidence interval for the combined effect is computed as

$$Lower\ Limit^* = \bar{T}_{.}^{*} - 1.96^* \ SE(\bar{T}_{.}^{*}) \qquad (3.19)$$

$$Upper\ Limit^* = \bar{T}_{.}^{*} + 1.96^* \ SE(\bar{T}_{.}^{*}) \qquad (3.20)$$

For Z- value, could be computed using

$$Z = \frac{\bar{T}_{.}^{*}}{SE(\bar{T}_{.}^{*})} \qquad (3.21)$$

The one-tailed p-value is area under the probability distribution function (pdf) both to the left of -|z|, and to the right of |z| given by

$p^* = \phi(z)$ and $p^* = 1 - \phi(z)$ (3.22)

And from the fact that $\phi(-z) = 1 - \phi(z)$ the two-tailed p-value by

$p^* = 2[1 - \phi|z|]$ (3.23)

Where $\phi(Z)$ is the standard normal cumulative distribution function

III. RESULTS AND DISCUSSION

Results of Meta-analysis results to evaluate the effectiveness performance of personalized recommendation systems that is used in online platforms.

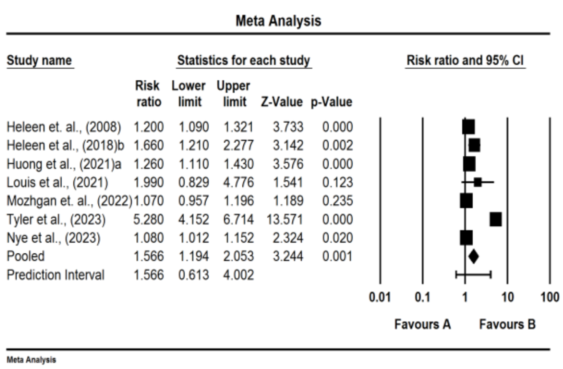


Figure 4: Result of Meta-analysis showing the pooled random-fixed effect model on meta-analysis on the effectiveness performance of personalized recommendation systems that is used in online platform.

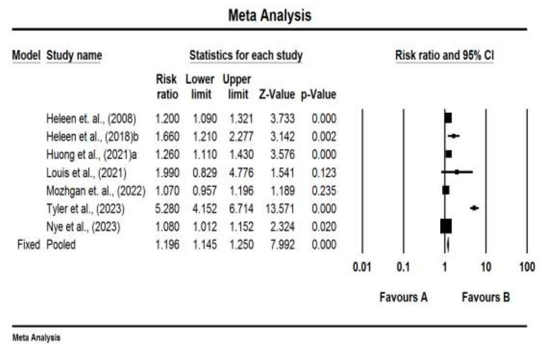


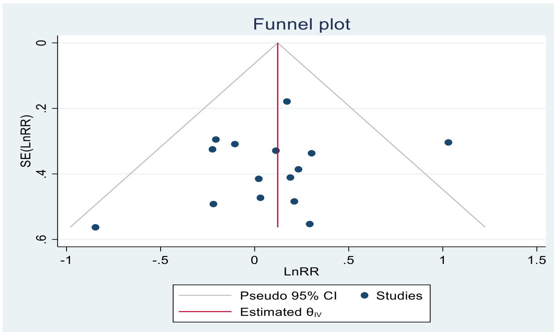
Figure 5: Result of Meta-analysis showing the pooled fixed effect model on meta-analysis on the effectiveness performance of personalized recommendation systems that is used in online platforms.

Interpretation of Meta-analysis result to evaluate the effectiveness performance of personalized recommendation systems that is used in online platforms.

The mean effect size is 1.566 with a 95% confidence interval of 1.194 to 2.053. The mean effect size in the universe of comparable studies could fall anywhere in this interval. The Z-value tests the null hypothesis that the mean effect size is 1.000. The Z-value is 3.244 with p = 0.001. Using a criterion alpha of 0.050, we reject the null hypothesis and conclude that in the universe of populations comparable to those in the analysis, the mean effect size is not precisely 1.000.

The Q-statistic provides a test of the null hypothesis that all studies in the analysis share a common effect size. If all studies shared the same true effect size, the expected value of Q would be equal to the degrees of freedom (the number of studies minus 1). The Q-value is 15.97 with 8 degrees of freedom and $p < 0.001$. Using a criterion alpha of 0.100, we can reject the null hypothesis that the true effect size is the same in all these studies. The I-squared statistic is 65.3%, which tells us that some 65.3% of the variance in observed effects reflects variance in true effects rather than sampling error. If we assume that the true effects are normally distributed (in log units), we can estimate that the prediction interval is 0.613 to 4.002. The true effect size in 95% of all comparable populations falls in this interval. Tau-squared, the variance of true effect sizes, is 0.114 in log units. Tau, the standard deviation of true effect sizes, is 0.338 in log unit.

Assessing publication bias and testing their symmetry using funnel plot.



Funnel plot of natural unit of standard difference mean and standard error for user behavior for personalized recommendation systems

From 6, the scatter plot of the natural logarithm of effect-size (LnSDM) against their natural logarithm standard errors SE(LnSDM). The estimated effect-size line (LnSDM) and the corresponding pseudo 95% confidence intervals are also plotted. The funnel plot is clearly symmetric, the plotted pseudo confidence interval lines are not genuine confidence interval limits, but they provide some insight into the spread of observed effect-sizes about the estimate of the overall effect-size. From figure 4.2.3 there is no heterogeneity since the studies are scattered within the confidence interval region which resembles an inverted funnel shape, hence there is no publication bias.

CONCLUSION

In this paper we have introduced meta-recommenders as a new way to help users find recommendations that are understandable, usable, and helpful. A series of controlled use experiments in the domain of movies indicates that users prefer that these systems provide recommendation data alongside the recommendations and prefer to have control to the selection of this data. Additionally, results suggest that users prefer the recommendations provided by these systems when compared with recommendations provided by "traditional" recommender systems. All told, we feel these results provide a meaningful foundation for the design of future meta recommenders.

RECOMMENDATIONS

It gives personalized controlled plans via the variation in controlled response and adverse reactions, personalized controlled plans based on individual patient profiles should be prioritized. This will help optimize outcomes and reduce the occurrence of severe mean effects. Furthermore, it enhanced monitoring and management of adverse reactionswith online user providers should implement more rigorous monitoring protocols to manage adverse reactions effectively. This could include pre-controlled evaluations, regular assessments during awareness and follow-ups to mitigate the impact of mean effects.

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