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Review

LGCM and PLS-SEM in Panel Survey Data: A Systematic Review and Bibliometric Analysis

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Abstract: The application of Latent Growth Curve Model (LGCM) and Partial Least Square Structural Equation Modeling (PLS-SEM) has gained much attention in panel survey studies. This study explores the distributions and trends of LGCM, and PLS-SEM used in panel survey data. It highlights the gaps in the current and existing approaches of PLS-SEM practiced by researchers in analyzing panel survey data. The integrated bibliometric analysis and systematic review were employed in this study. Based on the reviewed articles, the LGCM and PLS-SEM showed an increasing trend of publication in the panel survey data. Though the popularity of LGCM was more outstanding than PLS-SEM for the panel survey data, LGCM has several limitations such as statistical assumptions, reliable sample size, number of repeated measures, and missing data. This systematic review identified five different approaches of PLS-SEM in analyzing the panel survey data namely pre- and post-approach with different constructs, a path comparison approach, a cross-lagged approach, pre- and post-approach with the same constructs, and an evaluation approach practiced by researchers. None of the previous approaches used can establish one structural model to represent the whole changes in the repeated measure. Thus, the findings of this paper could help researchers choose a more appropriate approach to analyzing panel survey data.

Keywords: bibliometric; SLR; panel survey data; longitudinal survey; Latent Growth Curve Model (LGCM); PLS-SEM

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1. Introduction

Over the past few decades, various survey studies have been conducted using different types of survey designs. Many of them used cross-sectional survey design that is able to measure variation in the individuals of a population [1–4] at one point in time. However, in recent years, the development from cross-sectional to panel survey studies can be seen to escalate [5–7] in longitudinal studies. The panel survey data has been used widely in several areas such as education, medicine, psychology, behavior, and many more [8–10]. This type of study allows the researcher to measure variation at the individual level repeatedly on the same sample of units at different points of time. Through panel survey data, the trend and factors influencing those changes can also be observed.

From a methodological perspective, there are several methods that can be used to analyze cross-sectional survey data types. The most commonly used methods are based on Structural Equation Modelling (SEM). SEM offers two methods which are (i) covariance-based SEM (known as CB-SEM), and (ii) variance-based SEM (known as Partial Least Square (PLS-SEM)) method. These methods are often used to identify multiple statistical relationships simultaneously through visualization and model validation. It is more suitable for complex models compared to the traditional method such as Multiple Linear Regression and Analysis of Variance (ANOVA). CB-SEM and PLS-SEM have their own strengths and weaknesses depending on the data structures and assumptions of the methods.

While in the panel survey data, a method based on the CB-SEM framework known as Latent Growth Curve Model (LGCM) is commonly being used compared to the PLS-SEM. The LGCM has gained its popularity largely in behavioral sciences research. This method is widely used in many areas including social behavioral research, psychology, clinical, developmental, educational research, learning and memory, and personality [11–16]. The LGCM has the advantage of analyzing the developmental trajectory of a single person and capturing individual variations over time. This means the method can assess the changes in intra-individual (within the individual) as well as inter-individual (between individuals) variation. It can also identify the important predictor variables that contribute to the individual's growth change over time. Although LGCM listed several advantages, this method can still be improved as highlighted by [11,17,18]. Among the issues concerned are statistical assumptions, reliable sample size, number of repeated measures, and missing data. Despite its limitation, this method is still the choice of researchers for analyzing panel survey data compared to the PLS-SEM.

On the other hand, PLS-SEM only gained popularity in analyzing cross-sectional survey data but not in panel survey data. In a cross-sectional survey study, the PLS-SEM showed good performance in handling non-normal data and small sample size. According to [9], PLS-SEM showed higher robustness in situations of non-normal data and small sample size. It also shows a better result with a small sample size when a model has many constructs and a large number of items [19–21]. However, the use of PLS-SEM in panel survey data seems to be seemingly underrated as cross-sectional survey data, even though the PLS-SEM is good in handling several highlighted issues such as statistical assumptions and reliable sample size in LGCM. The previous approaches for panel survey data using PLS-SEM were unable to establish one structural model to represent the whole changes in the repeated measure. Current approaches also cannot capture the individual trajectory, mean of the trajectory of the sample or entire group, the evaluation of individual differences in trajectories, and assess the potential incorporation of predictors of individual differences in trajectories. A review of the previous approaches of these path analyses in longitudinal studies does not consider systematic literature review methodology [22]. Thus, there is a need to review the current and existing PLS-SEM approaches using SLR and Bibliometric analysis for panel survey data in identifying the gap in existing methods for improvement.

Hence, this study aimed to explore the distributions and trends of LGCM, and PLS-SEM used in panel survey data. It highlights the gaps in the current and existing approaches of PLS-SEM practiced by researchers in analyzing panel survey data. It focuses on answering the following research questions; (i) What is the distribution and trend of LGCM and PLS-SEM in a panel survey study? (ii) What are the reasons for the lack of application of PLS-SEM in panel survey data? and (iii) What is the existing framework or procedure of PLS-SEM in analyzing the panel survey data? This study employs the integrated bibliometric analysis and systematic review because the way of reviewing the existing literature is more systematic, and more comprehensive compared to the classical literature review [23–25]. Through a systematic review, further investigation and identification of the reasons for the lack of application for PLS-SEM in panel survey data can be discovered. Exploration of the existing framework or procedure of PLS-SEM could help the researcher to identify the method for improvement in analyzing the panel survey data.

2. Related Work

2.1. Panel Survey Data

A panel survey is a type of survey method that involves the process of gathering data from the same sample over a period of time. It is one of the longitudinal study types that is conducted over an extended period of time. The data collected from this panel survey are referred to as panel survey data. Panel survey data are commonly used to measure the behavior of people over time including their thoughts, attitudes, feelings, emotions, and many more [26–28]. It can measure the changes in behavior over time and examine the factors that influence that change. In the context of statistical methods, the LGCM and PLS-SEM are two methods that are used for analyzing the panel survey data. These two methods can handle this type of data since both can assess the measurement model (reliability and validity) and structural model. This is because these methods used Structural Equation Modeling as a basis of the framework and followed its criteria.

2.2. Latent Growth Curve Model

The latent Growth Curve Model (LGCM) created by [29,30] has grown to be a better method for addressing issues about individual behavior change and assessing the factors that contributed to the change simultaneously. The LGCM is a combination of the growth curve model (GCM) and structural equation modeling (CB-SEM). According to [31], the LGCM is a special case of confirmatory factor analysis (CFA) in CB-SEM and followed all underlying assumptions of CB-SEM. The growth of LGCM has become more popular in panel survey study since it can measure the changes in individuals and groups (known as trajectory) over time. Furthermore, it can also assess the factors that influence the trajectory.

2.3. PLS-SEM for Panel Survey Data

The PLS path modeling or PLS-SEM was created by [32,33] and some extensions were suggested by [34]. Over the last few decades, there have been numerous introductory articles on this methodology (e.g., [35–38]). However, in the panel survey studies, the application of this method is very limited compared to the cross-sectional studies [22]. This is because the exploration and the procedure of PLS-SEM for analyzing panel survey data are not consistent since it was used differently by the authors in several research articles [39–43].

3. Materials and Methods

This section explains the methodology used in this study. This study used an integrated systematic literature review (SLR) and bibliometric analysis for the review process [24,25,44].

3.1. Phase 1—Systematic Literature Review (SLR)

In the systematic review, the process of reviewing followed the review protocol, publication standard, or established guideline. The review protocol is equivalent to a research design in social sciences research. It is very important to decide which review protocol, publication standard, or established guideline is to be used at the beginning of the study [45]. This study adapted the established guideline by [46,47]. This established guideline was developed specifically for the education field. However, the guideline is suitable to be adapted in other fields, and it has been used in many other fields too. Based on this established guideline, this study started with the formulation of the research problems, followed by a systematic searching strategy (identification, screening inclusion, eligibility, and quality appraisal), data extracting, analyzing, and synthesizing (theme generation).

3.1.1. Formulating the Research Problems

The formulation of the research problems or the research questions for this study is based on the PICo [48,49]. PICo is used as a guideline to develop the research questions. PICo consists of three main concepts which are population or problem, interest, and context. In this study, the population can be described as panel survey data with several interests such as distributions and trends, limitations, and procedures. Then, this study described the context of statistical methods such as LGCM and PLS-SEM. Based on this concept, these research questions were created: “what are the distributions and trends of LGCM and PLS-SEM in a panel survey study?”, “what are the limitations of PLS-SEM in a panel survey data?" and "what is the existing framework or procedure of PLS-SEM in analyzing the panel survey data?".

3.1.2. Systematic Searching Strategies

In this stage, there are three main processes of searching strategies: (i) searching the literature (identification), (ii) screening the inclusion, and (iii) eligibility.

1. Searching the Literature (Identification)

Web of Science Core Collection (WoSCC) and Scopus are two bibliographic databases that are often regarded as the most comprehensive data sources for a variety of uses [50]. WoSCC was established around 2014 and previously known as the Web of Science (WoS) [51]. It was the first comprehensive international bibliographic database produced by Thomson Reuters in 1997. WoSCC consists of ten sub-databases and this study used eight sub-databases from the year 1992 to 2022. Among the sub-databases are Social Sciences Citation Index (SSCI), Science Citation Index Expanded (SCI-EXPANDED), Emerging Sources Citation Index (ESCI), Conference Proceedings Citation Index – Social Science & Humanities (CPCI-SSH), Arts & Humanities Citation Index (A&HCI), Conference Proceedings Citation Index – Science (CPCI-S), Book Citation Index – Social Sciences & Humanities (BKCI-SSH), and Book Citation Index – Science (BKCI-S). As a result, it eventually rose as the top choice of bibliographic database for bibliometric analyses, research appraisal, journal selection, and other duties [52]. In 2004, Elsevier introduced Scopus and established a solid reputation for dependability and earned a spot-on level with other comprehensive bibliographic databases over time [50,53]. Apparently, Scopus has a wider coverage, and thus it is useful for mapping a smaller research field as in the emerging topic of this study [54]. WoSCC and Scopus are also multidisciplinary and selective databases that are composed of a variety of specialized indexes, grouped according to the type of indexed content or by theme, [55]. Hence, both databases were employed as the bibliographic database for this study particularly to search for the right literature. For that reason, keywords are required to create the search string. In this study, the keywords were derived from the developed research questions as suggested by [56] as shown in Table 1. Based on this search string, a total of 3850 articles were retrieved automatically from the Scopus and WoSCC bibliographic databases. In addition, the stopping rule of searching the article is based on the rule of thumb as suggested by [57], where the search can stop when repeated search results are found in the same references, with no new results.

Table 1. Search string for the retrieved records.

Database	Search String
Scopus	TITLE-ABS-KEY(("panel survey" OR "longitudinal survey" OR "panel data" OR "longitudinal") AND ("partial least squares" OR "latent growth curve" OR "LGCM" OR "PLS Path" OR "PLS-SEM"))
WoSCC	TS=(("panel survey" OR "longitudinal survey" OR "panel data" OR "longitudinal") AND ("partial least squares" OR "latent growth curve" OR "LGCM" OR "PLS Path" OR "PLS-SEM"))

2. Screening the Inclusion

In the screening process, the articles were refined based on five criteria in the bibliographic database: (i) timeline, (ii) language, (iii) document type, (iv) subject area, and (v) type of data. The details for each criterion are explained in Table 2. In this stage, 2640 articles met the criteria and qualified for the next process.

Table 2. Inclusion and Exclusion Criteria.

Database Criteria	Inclusion	Exclusion
Timeline	All records in Scopus and WoSCC databases.	Other databases.
Language	English.	Other languages.
Document Type	Article, Article review, and Conference.	Books and chapters in a book.
Subject area	Psychology, Social Sciences, Business, Management, Accounting, Mathematics, **Economics**, and Multidisciplinary, Behavioral Sciences	Other subject areas in bibliographic databases of Scopus and WoSCC.
Method	LGCM, PLS-SEM, and Partial Least Squares.	Multilevel Linear Growth Curve Model, Bayesian Growth Curve Model, Repeated Measure ANOVA, Generalized estimating equations, and Mixed effect regression.
Type of data	Longitudinal survey and panel survey data.	Cross-sectional data.

3. Eligibility

The eligibility process involved the review of the title, keyword, and abstract. [58] suggested that a researcher should review the conclusion if the information in the abstract cannot give the general picture of the article. The selection of articles is based on the inclusion criteria (Table 2) contained in either the title, keyword, or abstract. After this selection process, the articles were checked for duplication according to the title and the redundant articles were removed. Hence, 1726 articles were selected after the removal process.

3.2. *Phase 2—Bibliometric Analysis*

The bibliometrics method was first introduced in 1969 by a scholar named Pritchard. The term bibliometric is elaborated as an information and library sciences research area which employs a quantitative approach and analyzes the bibliographical data of among others, the year of publication, country of origin, authors, etc. [59]. The bibliometric method employs quantitative analysis of empirical data published in prior literature to study the trends of publication within various research domains. Furthermore, it enables researchers to examine the body of literature in their field of study and identify the major themes [54,60]. Using bibliometric analysis allows researchers to explore the trends, reader usage, citation pattern, knowledge base, author network, and significance of the subject [61]. Bibliometric analysis is often combined with science mapping techniques to visualize the intellectual structure of a particular research field [62]. Visualization requires visual tools such as VosViewer, Gephi, or Pajek, which have been used extensively in management and science research. In this study, bibliometric analysis was employed to analyze citation-based analysis, co-word analysis or keyword co-occurrence analysis, and co-authorship analysis, which are considered the most common ones using this method.

3.2.1. Data Extraction

The process of data extraction was followed by data requirements of bibliometric analysis such as the author's names, citations, titles, journals, DOI, references, abstracts, keywords, and author affiliations [46]. The data from each bibliographic database was extracted into an excel file and merged following the Scopus format. Then, data were exported into VOSviewer for constructing and visualizing the information. Next, the thresholds such as the minimum number of publications, citations, and occurrence of keywords were specified for analysis of science mapping.

3.2.2. Analyzing and Synthesizing the Data

The bibliometric analysis consists of two techniques which are performance analysis and science mapping. This study used performance analysis to determine the distribution and the trend of the publication related to the panel survey data. Besides that, the analysis of science mappings such as Co-authorship, Keyword Co-occurrence, Citation, and Co-citation Analysis was used to examine the relationships between the research constituents [46].

3.3. Phase 3—Content Analysis

In this phase, the procedure from SLR, which is quality appraisal, is used to select suitable articles for content analysis. The content analysis was used to generate the themes to explain the findings related to the PLS-SEM in panel survey data.

3.3.1. Quality Appraisal

In this stage, selected articles that are related to the PLS-SEM were chosen based on citation analysis in the bibliometric analysis. The total number of articles related to the PLS-SEM was 296, after the eligibility process. However, for the content analysis, only the top 100 most cited articles were included in the quality appraisal process. The quality appraisal is very important in the systematic literature review as suggested by [63]. In this process, the full articles were examined by the research team to select the most suitable articles that are related to the procedure of PLS-SEM in analyzing the panel survey data. After the quality appraisal process, 34 articles were selected for the final review (Figure 1, Table A1).

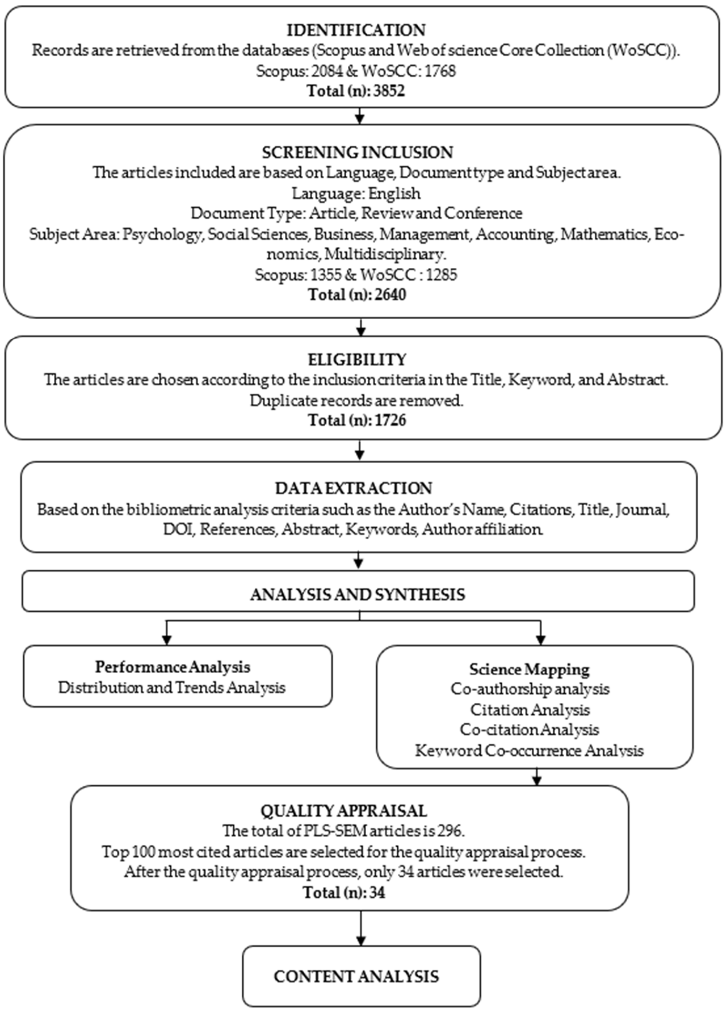

Figure 1. The Flow Diagram of Reviewing Process.

3.3.2. Theme Generation

In this stage, the theme was generated based on the 34 articles reviewed. The themes were classified into PLS-SEM approaches and their imitations, and the procedure of the approaches.

4. Results

This section discusses the distributions and trends of LGCM and PLS-SEM in panel survey data, the limitations of PLS-SEM in panel survey data, and the existing framework or procedure of PLS-SEM in analyzing the panel survey data. This discussion reflects the research questions stated in the early section.

4.1. Distributions and Trends

To answer the first research question, the discussion discovers the growth of publications, co-authorship, citation, co-citation, and co-occurrences of keywords.

4.1.1. Growth of Publications

Figure 2 shows the annual growth of publications related to the panel survey data that used the Latent Growth Curve Model (LGCM) and PLS-SEM as the main statistical methods in the analysis. These publications were retrieved from Scopus and Web of Science Core Collection (WoSCC) databases from 1986 to 2022. Based on the graph, the publications show an increasing trend from 2006 to 2022. Figure 2 also shows the annual growth of publications related to LGCM and PLS-SEM separately. Both annual growths of publications show an increasing trend from 2006 to 2022. However, LGCM is more outstanding compared to PLS-SEM as a statistical method to analyze panel survey data.

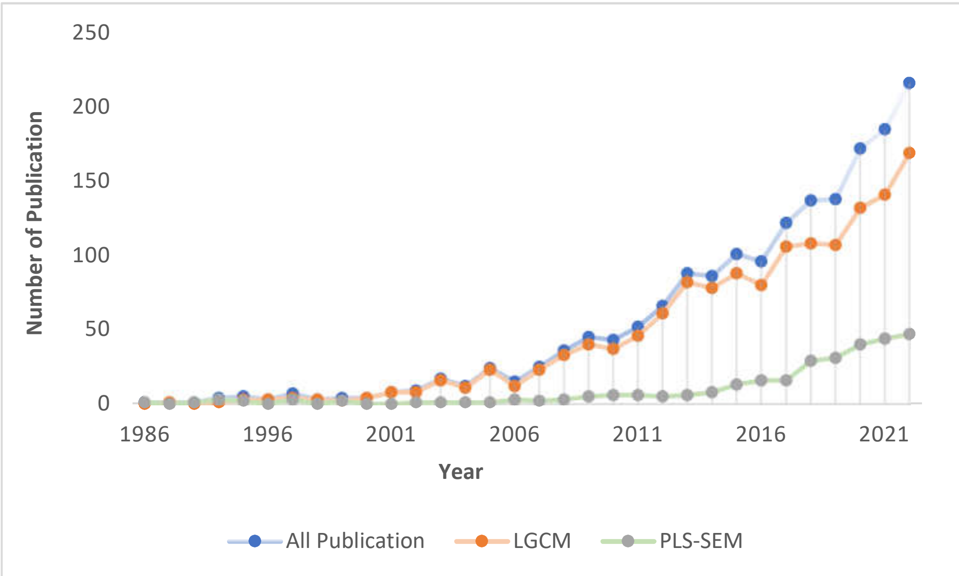

Figure 2. Annual growth of publications (Scopus & WoSCC databases, 1986–2022).

All 1726 retrieved articles were published in 638 different journals, with 2.71 articles per journal on average. Out of these 638 journals, 365 (57.21%) published only one article, 118 (18.59%) published two articles, and 115 (24.29%) published more than two articles. Table 3 shows the top ten journals contributing to the panel survey data. Based on the total citations, Development Psychology journal is the most cited journal with 4231 citations, followed by Structural Equation Modeling, and Psychology and Aging journal with 1267 and 1061 citations respectively. However, in terms of total publications, no journals show an outstanding performance since the number of publications is close to each journal.

Table 3. Top 10 journals contributing to the panel survey data.

Source (Journal)	Total Publications	Total Citations
Developmental Psychology	51	4231
Structural Equation Modeling	30	1267
Journal of Youth and Adolescence	29	930
PLoS ONE	28	498
Psychology and Aging	25	1061
Journal of Affective Disorders	25	234
Journal of Abnormal Child Psychology	22	1043
Journals of Gerontology	21	584
Frontiers in Psychology	20	200
Journal of Adolescence	19	741

4.1.2. Co-Authorship Analysis

The main purpose of co-authorship analysis is to examine the interactions among scholars related to the panel survey data. Based on the retrieved records, 4481 authors contributed 1726 articles in the panel survey data. Out of 4481, only 459 authors met the threshold of at least 2 publications and 25 citations. Figure 3 shows that the connection between clusters is small and only 8 clusters are connected to each other. This result indicates that the majority of productive authors are independent researchers and the cluster formed by the researchers working on the panel survey data is weak, and the scale of co-authorship cooperation is small and limited.

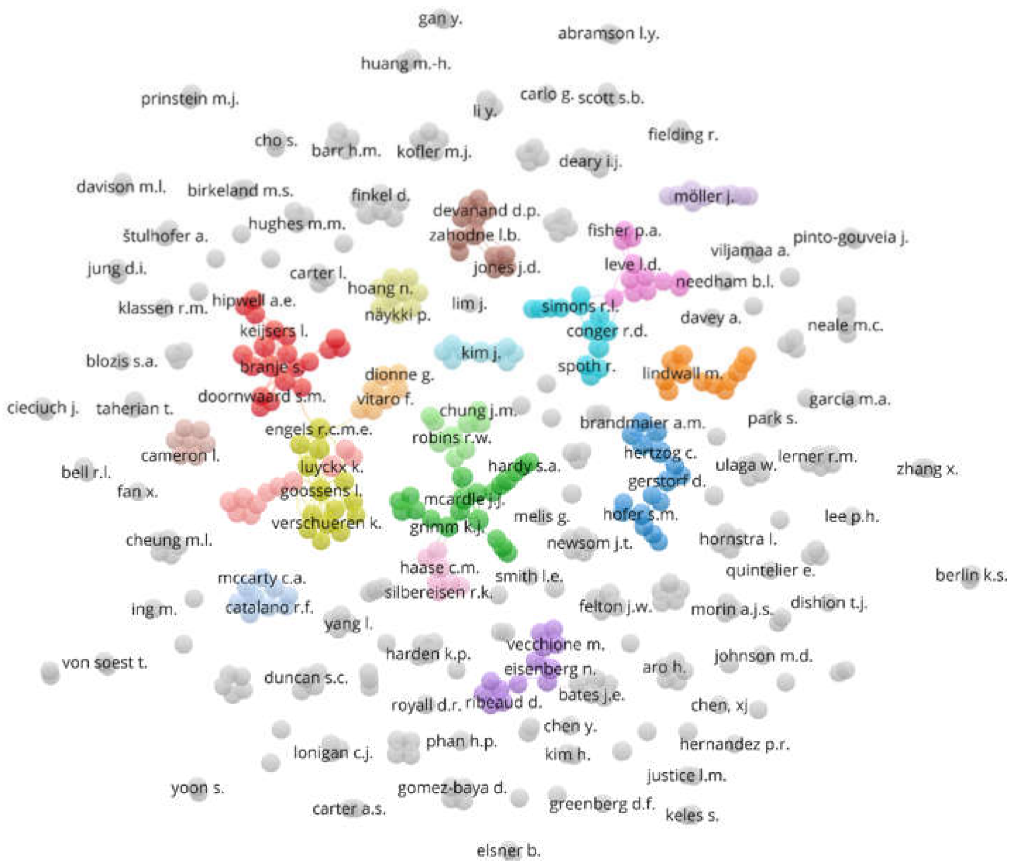

Figure 3. Co-authorship network map in the field of panel survey data.

4.1.3. Citation Analysis

The citation analysis was used to identify the most influential publications in the research field. The purpose is to gain an understanding of the intellectual dynamics of the research field. In this analysis, the most influential articles were selected based on the highest number of total citations and analyzed according to two statistical methods which are LGCM and PLS-SEM. Tables 4 and 5 show the lists of the top 5 most cited articles in LGCM and PLS-SEM. McArdle J.J and Epstein D. (1987) is the most cited article according to LGCM, with 653 total citations. While in PLS-SEM, Limayen M and Cheung C.M.K. (2008) is the most cited article with 369 total citations.

Table 4. The most cited articles related to LGCM.

Rank	Authors	Year	DOI	Citations
1	McArdle J.J., Epstein D.	1987	10.2307/1130295	653
2	Ge X., Lorenz F.O., Conger R.D., Elder Jr. G.H., Simons R.L.	1994	10.1037/0012-1649.30.4.467	625
3	Plutzer E.	2002	10.1017/S0003055402004227	549
4	McArdle J.J., Ferrer-Caja E., Hamagami F., Woodcock R.W.	2002	10.1037/0012-1649.38.1.115	401
5	Wang M.	2007	10.1037/0021-9010.92.2.455	388

Table 5. The most cited article related to PLS-SEM.

Rank	Authors	Year	DOI	Citations
1	Limayem M., Cheung C.M.K.	2008	10.1016/j.im.2008.02.005	369
2	Baer J.S., Sampson P.D., Barr H.M., Connor P.D., Streissguth A.P.	2003	10.1001/archpsyc.60.4.377	284
3	Wong V.W.-S., Tse C.-H., Lam T.T.-Y., Wong G.L.-H.	2013	10.1371/jounal.pone.0062885	217
4	Dodge K.A., Malone P.S., Lansford J.E., Shari M., Pettit G.S., Bates.	2009	10.1111/j.15405834.2009.00528.x	210
5	Hennig-Thurau T., Henning V., Sattler H.	2007	10.1509/jmkg.71.4.001	208

In the context of relationships among publications, most of the authors work independently, which indicates a weak relationship. The relationships among authors according to the citations can be seen in Figure 4. The citation analysis for 1726 articles revealed that 494 articles met the threshold of 25 minimum number of citations of the document. The network visualization map shows that only a few clusters are connected to each cluster, even though those publications have the highest number of citations such as McArdle J.J. and Epstein D. (1987).

4.1.4. Co-Citation Analysis

Co-citation analysis of cited references was performed as well. By definition, the reference can be a co-citation if the two documents are cited together by another document [63]. As shown in Figure 5, each point represents the cited author, and the color of the points is according to the number of co-citations. A total of 88,731 cited authors were detected, and only 800 authors met the threshold in which the minimum citation of an author is 800. As seen in Figure 5, 800 authors formed 7 different clusters that provide information related to the co-citation of this study. Overall, most of the co-citations are related to statistical methods such as the Latent growth curve model, evaluation in structural equation modeling, evaluation in PLS-SEM, and procedure in the simulation study. The highest total link strength in co-citation analysis is Muthen and McArdle, and the article is related to the simulation study and latent curve analysis.

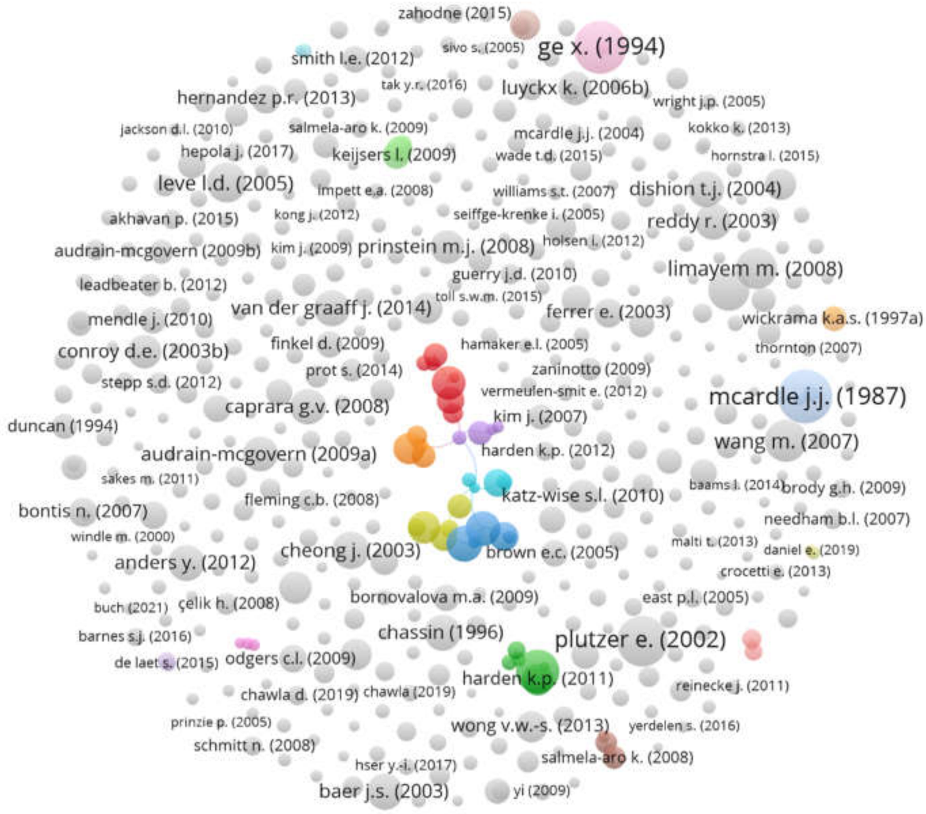

Figure 4. Network visualization map of citations based on the documents.

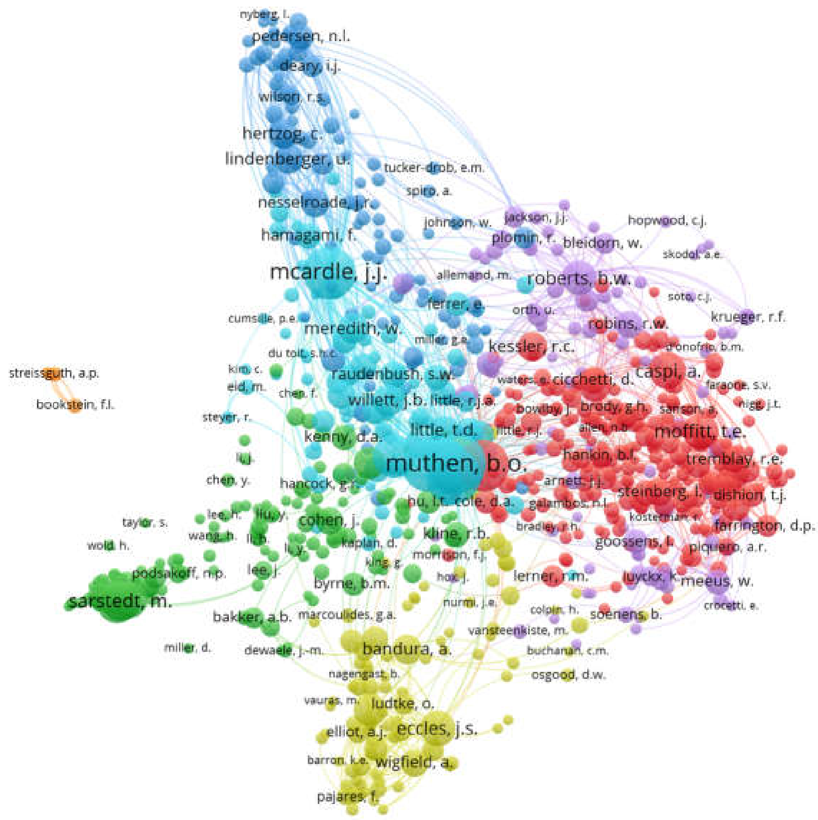

Figure 5. Network visualization map of co-citation of cited authors.

4.1.5. Keyword Co-Occurrence Analysis

The co-occurrence analysis focuses on the examination of the actual content of the publications based on the words derived from the author's keyword. This analysis can determine the trend of research topics in recent years. Figure 6 shows the network visualization map of the co-occurrence of keywords related to the panel survey data. Based on this analysis, 3875 keywords were retrieved from 1725 articles. However, there were only 49 keywords that met the minimum threshold of occurrences number of at least 10. As seen in Figure 6, 49 keywords formed 9 different clusters that provided information about the related topic of this study. The largest cluster was the red and green clusters which consisted of 11 keywords for each cluster. In addition, Table 6 shows the list of keywords as well as their co-occurrence frequencies in each cluster. In the context of the research topic, longitudinal study and adolescence showed the highest co-occurrences in this study with 292 and 169 repeated keywords, respectively. While in the context of statistical method, the Latent growth curve model was the most used in the analysis, with 294 co-occurrences keywords, followed by structural equation modeling, PLS-SEM, and partial least squares with 22, 14, and 11 respectively. Besides, the keywords in the same cluster shared a similar topic. Generally, most of the research topic for each cluster is related to mental health, psychology, child and adolescent development, and lifestyle.

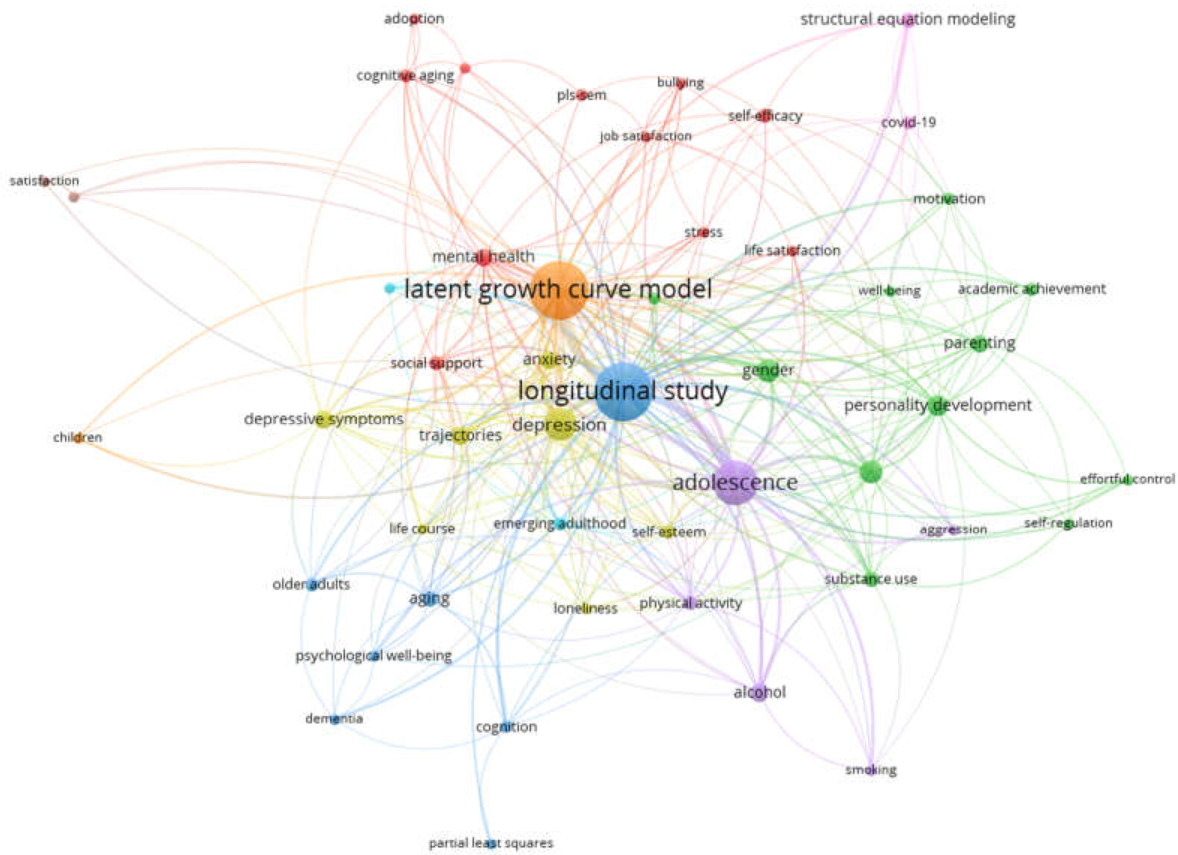

Figure 6. The network visualization map of co-occurrences of keywords.

To examine the trend of research topics in the recent year, an overlay visualization map was produced. Figure 7 shows the co-occurrences of the keywords according to the time (in years). Based on the overlay visualization map, there were a few research topics in recent years, such as mental health, life satisfaction, cognition, aggression, effortful control, children, social media, and COVID-19. In the context of statistical methods, PLS-SEM has been used in recent years to analyze the panel survey data.

Table 6. Co-occurrence of author keyword in panel survey data.

Cluster 1 (Red)	**Cluster 2 (Green)**	**Cluster 3 (Blue)**
Mental Health (27)	Developmental Trajectories (48)	Longitudinal Study (292)
Self-Efficacy (18)	Gender (47)	Aging (22)
Social Support (18)	Personality Development (38)	Older Adults (15)
Cognitive Aging (16)	Parenting (26)	Cognition (14)
PLS-SEM (14)	Substance Use (20)	Psychological Well-Being (12)
Adoption (12)	Academic Achievement (15)	Dementia (11)
Life Satisfaction (12)	Growth Curve Modeling (14)	Partial Least Squares (11)
Stress (12)	Motivation (14)	**Cluster 6 (Light Blue)**
Bullying (11)	Effortful Control (10)	Emerging Adulthood (16)
Education (11)	Self-Regulation (10)	Delinquency (12)
Job Satisfaction (10)	Well-Being (10)	**Cluster 7 (Orange)**
Cluster 4 (Yellow)	**Cluster 5 (Purple)**	Latent Growth Curve Model (294)
Depression (91)	Adolescence (169)	Children (10)
Trajectories (32)	Alcohol (32)	**Cluster 8 (Brown)**
Depressive Symptom (31)	Physical Activity (19)	Satisfaction (10)
Anxiety (28)	Aggression (10)	Social Media (10)
Self-Esteem (18)	Smoking (10)	**Cluster 9 (Pink)**
Life Course (12)		Structural Equation Modeling (22)
Loneliness (12)		COVID-19 (15)

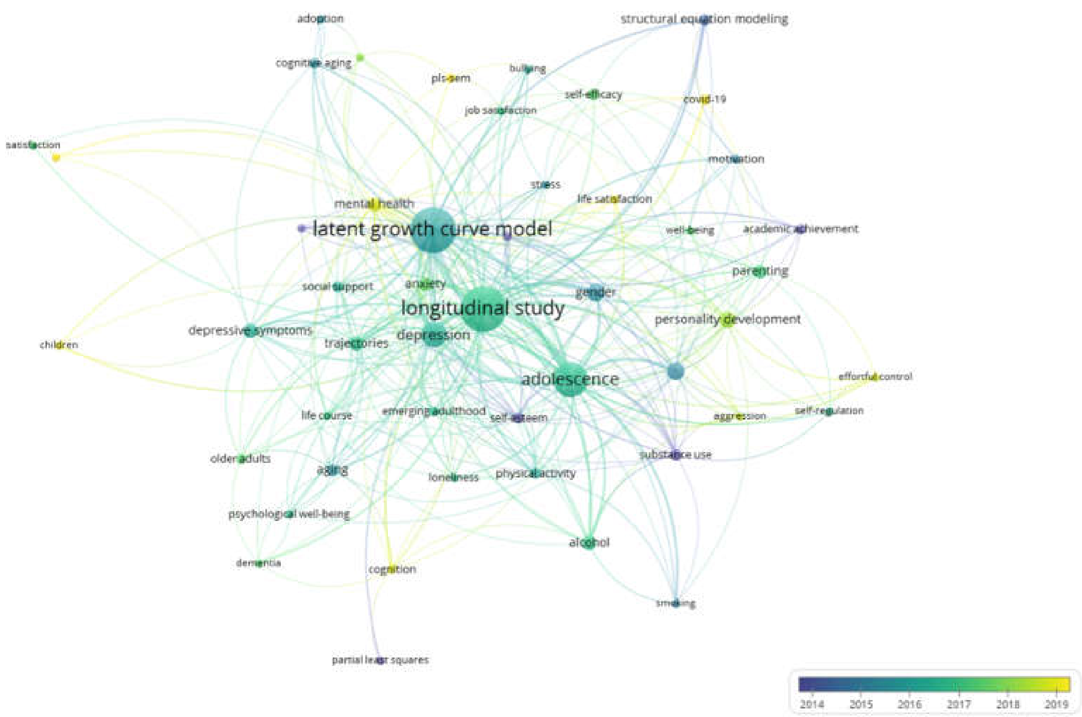

Figure 7. The overlay visualization map of keywords according to year.

Overall, bibliometric analysis has fulfilled the first research question related to the trend of the Latent growth curve model (LGCM) and PLS-SEM in panel survey data. The result shows that the distribution, trend, and application of LGCM are more outstanding than PLS-SEM in analyzing the panel survey data. To answer the next two research questions, content analysis was employed. Content analysis is focused on exploring the PLS-SEM in analyzing the panel survey data. The reason behind exploring the PLS-SEM in the panel survey data is due to the bibliometric analysis that shows the development of this method is not well developed, even though this method has good potential in handling panel survey data.

4.2. Themes Generation

To answer the other two research questions related to the limitations of PLS-SEM in panel survey data and the procedure of the existing approach of PLS-SEM in panel survey data, content analysis was employed. This section explains the details of content analysis on the PLS-SEM approach for panel survey data based on the selected top 100 most cited papers. The explanation of the content analysis is divided into two different themes: (i) identification of PLS-SEM approaches and their limitations, and (ii) procedures of the method.

4.2.1. Identification of PLS-SEM Approaches and Their Limitations

The exploration of the PLS-SEM approach is explained according to the evaluation of the measurement, and the structural model. Based on the reviewed articles, most of the researchers used the standard procedure to evaluate the measurement model as suggested by [64]. The measurement model involved the evaluation of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

However, when evaluating the structural model, most of the top researchers use different approaches and procedures. As a summary, five approaches and procedures are identified to be used by researchers. The first approach is suitable for two periods of time and uses the different latent constructs at the pre-evaluation and post-evaluation named *pre- and post-approaches with different constructs*. The main purpose of this approach is to evaluate relationships between the exogenous variable at pre-evaluation, and the endogenous variable or outcome at post-evaluation. The relationship was evaluated using partial least squares (PLS) in the structural model. The second approach is known as the *Path Comparison approach*, and it is suitable for two periods of time. This approach uses the same latent construct at the initial (t_0) and end (t_1) of the evolution. This approach can measure the relationship of the latent construct using path analysis and the impact of time on the PLS model using a t-test. The third approach is named the *Cross-Lagged Panel Method (CLPM)*, and the main purpose is to measure the direction, strength, and cause-effect relationship among latent constructs over time. This method is also suitable for two periods of time and uses the same construct at time 1 and time 2. The fourth approach also involves two periods of time and measures the same latent constructs at pre-evaluation and post-evaluation named *pre- and post-approaches with the same constructs.* The difference between this method compared to the other three is regarding the latent score used to develop the PLS model. This method uses the differences in scores from time 1 and time 2 to develop the PLS model. The fifth approach is the *evaluation approach* which involves more than two waves of time and uses the same constructs for evaluating participants over time. The main purpose is to evaluate the direct and indirect effects over time. This approach uses path analysis to evaluate the direct effects between latent constructs and indirect effects over time using a bias-corrected confidence interval.

Though there are five different approaches of PLS-SEM in analyzing the panel survey data, these approaches still have limitations and spaces for improvement. The obvious limitation for models 1, 2, 3, and 4 is related to the number of waves for the study, since these approaches are only suitable for two periods of time. In addition, these four models focus on the pre- and post-evaluations and do not measure the evaluations of effects over time. Besides that, model 5 has the limitation in evaluating the growth of trajectory even though this method is capable of handling studies with more than two periods of time. This model does not have one structural model to represent the whole changes in the repeated measure. In addition, this model cannot capture an individual trajectory, the mean of the trajectory of the sample or entire group, the evaluation of individual differences in trajectories, and assess the potential incorporation of predictors of individual differences in trajectories. Furthermore, this model is not flexible to handle the latent constructs simultaneously as independent and dependent in the same model, allowing for complex representations of growth and correlations of change. Table 7 shows the summary of the five different approaches practiced by researchers in analyzing panel survey data.

Table 7. Summary of approaches practiced in analyzing a structural model.

Type of Model	Descriptions	Limitations	Authors
Model 1: Pre and Post approach with different construct.	• Two periods of time. • Pre and Post approach with different constructs. • Used path analysis.	• Not suitable for more than two periods of time. • Cannot measure the evaluation of effect over time.	[65–67]
Model 2: Path Comparison approach.	• Two periods of time. • Using the same construct at the first and the second time of survey. • Analyze two models separately according to time (t_0 and t_1). • Used path analysis. • Comparing these two models using a *t*-test.	• Not suitable for more than two periods of time. • Cannot evaluate the changes in one structural model. • .	[68]
Model 3: Cross-lagged approach.	• Two periods of time. • Using the same construct at the first and the second time of survey. • Used Cross-lagged approach.	• Not suitable for more than two periods of time. • Cannot assess the growth trajectories. • Required a few assumptions.	[69]
Model 4: Pre and Post approach with same construct.	• Two periods of time. • Used paired *t*-test for evaluating the differences between indicators (t_1 and $t_{2)}$. • Evaluating the effect between changes of constructs based on the value of differences between indicators. • Used path analysis.	• Not suitable for more than two periods of time. • Cannot assess the growth of trajectories.	[43]
Model 5: Evaluation approach.	• More than two periods of time. • Measured direct effect and carry-over effect. • Used paired t-test, path analysis, and bias-corrected confidence interval.	• Do not have one structural model. • Cannot assess model fit. • Cannot assess the whole changes in one structural model. • Cannot assess individual trajectories and factors influencing those changes simultaneously.	[41,70,71]

4.2.2. Procedure of the Approaches

This section explains the details of the procedure for several PLS-SEM approaches practiced by the researchers in analyzing the panel survey data. The procedure of the approach is explained according to the data collection phase and analysis phase. Table 8 shows the summary of the procedure for five approaches in PLS-SEM to analyze the panel survey data.

Table 8. The procedure of the PLS-SEM approach in analyzing panel survey data.

Type of Model	Procedure	Articles
Model 1: Pre and Post approach with different constructs.	**Data collection phase:** **Time 1:** Participants' initial feedbacks will be evaluated. ↓ **Time 2:** Participants' full feedbacks will be evaluated using different constructs. **Analysis phase:** ↓ **Measurement Model** • Evaluate the reliability and validity of each construct. ↓ **Structural Model** • Develop one PLS model.	[65–67]
Model 2: Path Comparison approach.	**Data collection phase:** Participants will be evaluated two times using the same construct. ↓ **Analysis phase:** **Measurement Model** • Evaluate the reliability and validity of each construct at time 1 and time 2. ↓ **Structural Model** • Develop two PLS models separately according to time. • Compare these two PLS models using t-test.	[68]
Model 3: Cross-lagged approach.	**Data collection phase:** Participants will be evaluated two times using the same construct. ↓ **Analysis phase:** **Measurement Model** • Evaluate the reliability and validity of each construct for time 1 and time 2. ↓ **Structural Model** • Compare the mean scores between the constructs of time 1 and time 2. • Cause-effect relationships between constructs using cross-lagged panel.	[69]

Table 8. *Cont.*

Type of Model	Procedure	Articles
Model 4: Pre and Post approach with same construct.	**Data collection phase:** Participants will be evaluated two times using the same construct. **Analysis phase:** **Measurement Model** • Evaluate the reliability and validity of each construct for time 1 and time 2. **Structural Model** • Comparison of indicators from time 1 and time 2 using paired t-test. • Calculate the differences of indicators between time 1 and time 2.	[43]
Model 5: Evaluation Approach.	**Data collection phase:** Participants will be evaluated more than two times using the same construct. **Analysis phase:** **Measurement Model** • Evaluate the reliability and validity of each construct according to the time. **Structural Model** • Develop one PLS model according to time. • Test the changes in path coefficients over time. • Test the changes in the level of construct using paired t-test.	[41,70,71]

Model 1: Pre and Post Approach with Different Construct

This approach involves two phases of time in the data collection procedure. At time 1, the participants will be evaluated using the first set of questionnaires that consist of exogenous variables. The different sets of questionnaires that consist of the endogenous variable will be used for the second evaluation. In the analysis phase, the measurement and structural model will be evaluated. All the latent constructs will be evaluated based on reliability and validity. For the structural model, one PLS model will be established together with the path coefficients to perform the bootstrap resampling procedure to examine the significance of the paths.

Model 2: Path Comparison Approach

For this approach, the participants will be evaluated two times with the same questionnaire. In the measurement model, the reliability and validity for each construct at time 1 and time 2 will be developed separately. For the structural model, two PLS models will be developed separately according to the time (time 1 and time 2). Then, calculate the *t*-test using the formula suggested by [72] for comparing the corresponding path coefficient in both models. This analysis will examine the strength of the relationship between the paths over time.

Model 3: Cross-Lagged Approach

The procedure of this approach for the data collection phase and the measurement model evaluation is the same as Model 2. For the structural model, the analysis starts with the mean score comparison between latent construct time 1 and time 2. The purpose is to determine whether the mean score of the latent construct at time 2 will be higher than at time 1. Next, to determine the cause-effect relationship between latent constructs, the cross-lagged panel model will be employed.

Model 4: Pre and Post Approach with the Same Construct

The procedure of this approach for the data collection phase and measurement model evaluation is also the same as Models 2 and 3. For the structural model, the analysis starts with the comparison of the indicator of latent construct between time 1 and time 2 using paired *t*-test. If the result of the paired t-test has significant differences, then the new indicators are computed based on the differences between indicators at time 1 and time 2. Next, one PLS model will be developed based on the new indicators to determine the effects between change constructs.

Model 5: Evaluation Model

The data collection phase involves more than two periods of time with the same questionnaire. For the measurement model, the constructs will be evaluated according to the time. While in the structural model, the analysis starts by developing one PLS model for each period of time. In this stage, the direct effect and carry-over effect will be examined based on the path analysis. Then, to test the changes in the path coefficient over time, the bias-corrected confidence interval is computed. Next, paired *t*-test of the changes in the level of the construct over time is computed.

5. Discussion

Structural Equation Modeling (SEM) is one of the flexible methods for analyzing survey data. This method is used as a statistical tool for evaluating the relation between latent and observed variables [73]. SEM can be defined as a combination of several multivariate analysis techniques [74], such as path analysis [75] and the common factor or latent variable model [76]. Thus, this study reviewed the methodology that used SEM as a base framework for analyzing panel survey data. There are two methods that have been discovered in this study which are LGCM and several approaches in the PLS-SEM. The trend of publications related to the panel survey data is increasing over the year. The findings show that the application of LGCM is preferable compared to the PLS-SEM in analyzing the panel survey data. We can see the pattern in the bibliometric analysis where the findings are dominated by the LGCM. This is because the ability and flexibility of LGCM in handling panel survey data are better than the PLS-SEM. Among the ability of LGCM, it can describe the developmental trajectory of a single person and capture individual variations over time. In other words, this method can assess the changes in intra-individual (within the individual) as well as inter-individual (between individuals) variation. LGCM can also identify the important predictor variables that contribute to the individual's growth change over time. [77] described the several advantages of LGCM which permits the investigation of inter-individual differences in change over time and allows the researcher to investigate the antecedents and consequences of change. LGCM also provides group-level statistics such as mean growth rate and mean intercept, can test hypotheses about specific trajectories, and allows the incorporation of both time-varying and time-invariant covariates. This could be the main reason why LGCM is preferable compared to the PLS-SEM, even though it has several limitations. According to [22], the existing approaches of PLS-SEM in panel survey data still have limitations. The approaches also show a lack of flexibility in analyzing the panel survey data in one structural model. Thus, this study employed content analysis to identify the existing approaches of PLS-SEM in analyzing panel survey data and its limitations.

The findings show that there are five existing approaches of PLS-SEM that have been used in analyzing panel survey data. Among the existing approaches of PLS-SEM, the Evaluation approach is the most flexible approach in analyzing panel survey data. Thus, this study discussed this approach more than the other four approaches. This approach consists of three stages in analyzing the panel survey data. The analysis measured the direct effect and the special effect which is the carry-over-effect. Carry-over-effects are effects from one construct at one point in time to the same construct at a subsequent point in time [78]. In stage one, the direct effect and carry-over-effect are assessed by estimating the single PLS model separately across the time. With this, the separate direct effect between the endogenous and exogenous predictors across time can be assessed. Hence, one structural model to access the whole changes (trajectories) and the factors that influence those changes simultaneously cannot be established. In the second stage, the multi-group analysis is employed to assess the strength of direct effects and the carry-over-effects over time. This strength is measured by the changes in the size of the path coefficient and bias-corrected confidence interval. The limitation at this stage is that the factors that influence those changes in the carry-over-effect simultaneously in one structure modal cannot be measured. In the last stage, paired t-test is employed to assess the mean difference between the constructs. The limitation in this stage is that only the mean difference for two points at a time for each construct can be assessed. In addition, the paired t-test requires a few assumptions and the most concern for the researcher is the distributional assumption. Hence, all these stages in the Model 5 approach do not have one structural model to represent the whole changes in the repeated measure. In addition, current approaches cannot capture the individual trajectory, mean of the trajectory of the sample or entire group, the evaluation of individual differences in trajectories, and assess the potential incorporation of predictors of individual differences in trajectories. Consequently, with all these limitations, PLS-SEM is less frequently used for analyzing panel survey data.

6. Conclusions

In conclusion, this study explored the distributions and trends of publications related to the panel survey data. This study also explored the trends of publications according to the Latent Growth Curve Model (LGGM) and PLS-SEM in analyzing the panel survey data. The records were retrieved from the bibliographic databases of Scopus and Web of Science Core Collection (WoSCC). The trends of publications related to the panel survey data showed an increasing trend. However, in the context of the statistical method, the LGCM is preferable compared to the PLS-SEM in analyzing the panel survey data, even though the LGCM has several limitations as highlighted in previous studies. This is because the PLS-SEM shows a lack of capability in handling panel survey data, even though it has five different approaches in analyzing them. The most flexible approach of the PLS-SEM in handling panel survey data is model 5 since it can measure the direct effect, carry-over effect, and the changes of path coefficients over time. However, based on the review, this approach still has some space for improvement. This method cannot capture an individual trajectory, the mean of the trajectory of the sample or entire group, the evaluation of individual differences in trajectories, and assess the potential incorporation of predictors of individual differences in trajectories. Besides, these current approaches are not as flexible as LGCM since it has the ability to use variables simultaneously as independent and dependent in the same model. Therefore, this systematic review could help researchers choose a more suitable method to analyze panel survey data.

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Appendix A

Table A1. List of Evaluated Articles in Content Analysis.

No	Authors	Title	Year	Journal	DOI
1	Limayem M., Cheung C.M.K.	Understanding information systems continuance: The case of Internet-based learning technologies	2008	Information and Management	10.1016/j.im.2008.02.005
2	Baer J.S., Sampson P.D., Barr H.M., Connor P.D., Streissguth A.P.	A 21-year longitudinal analysis of the effects of prenatal alcohol exposure on young adult drinking	2003	Archives of General Psychiatry	10.1001/archpsyc.60.4.377
3	Bontis N., Booker L.D., Serenko A.	The mediating effect of organizational reputation on customer loyalty and service recommendation in the banking industry	2007	Management Decision	10.1108/00251740710828681
4	Islam A.K.M.N.	Investigating e-learning system usage outcomes in the university context	2013	Computers and Education	10.1016/j.compedu.2013.07.037
5	Barnes S.J., Mattsson J., Sørensen F.	Remembered experiences and revisit intentions: A longitudinal study of safari park visitors	2016	Tourism Management	10.1016/j.tourman.2016.06.014
6	Nelson B., Martin R.P., Hodge S., Havill V., Kamphaus R.	Modeling the prediction of elementary school adjustment from preschool temperament	1999	Personality and Individual Differences	10.1016/S0191-8869(98)00174-3
7	Hannula-Sormunen M.M., Lehtinen E., Räsänen P.	Preschool Children's Spontaneous Focusing on Numerosity, Subitizing, and Counting Skills as Predictors of Their Mathematical Performance Seven Years Later at School	2015	Mathematical Thinking and Learning	10.1080/10986065.2015.1016814
8	Bronstein P., Ginsburg G.S., Herrera I.S.	Parental predictors of motivational orientation in early adolescence: A longitudinal study	2005	Journal of Youth and Adolescence	10.1007/s10964-005-8946-0
9	Sosik J.J., Potosky D., Jung D.I.	Adaptive self-regulation: Meeting others' expectations of leadership and performance	2002	Journal of Social Psychology	10.1080/00224540209603896
10	Chen C.-P., Lai H.-M., Ho C.-Y.	Why do teachers continue to use teaching blogs? the roles of perceived voluntariness and habit	2015	Computers and Education	10.1016/j.compedu.2014.11.017
11	Benitez J., Chen Y., Teo T.S.H., Ajamieh A.	Evolution of the impact of e-business technology on operational competence and firm profitability: A panel data investigation	2018	Information and Management	10.1016/j.im.2017.08.002
12	Gupta V.K., Huang R., Niranjan S.	A longitudinal examination of the relationship between Team Leadership and Performance	2010	Journal of Leadership and Organizational Studies	10.1177/1548051809359184

Table A1. *Cont.*

No	Authors	Title	Year	Journal	DOI
13	Palos-Sanchez P., Saura J.R., Martin-Velicia F.	A study of the effects of programmatic advertising on users' concerns about privacy overtime	2019	Journal of Business Research	10.1016/j.jbusres.2018.10.059
14	Gegenfurtner A.	Dimensions of Motivation to Transfer: A Longitudinal Analysis of Their Influence on Retention, Transfer, and Attitude Change	2013	Vocations and Learning	10.1007/s12186-012-9084-y
15	Wei Y., Zhu X., Li Y., Yao T., Tao Y.	Influential factors of national and regional CO2 emission in China based on combined model of DPSIR and PLS-SEM	2019	Journal of Cleaner Production	10.1016/j.jclepro.2018.11.155
16	Palos-Sanchez, P; Saura, JR; Martin-Velicia, F	A study of the effects of programmatic advertising on users' concerns about privacy overtime	2019	Journal Of Business Research	10.1016/j.jbusres.2018.10.059
17	Roemer E.	A tutorial on the use of PLS path modeling in longitudinal studies	2016	Industrial Management and Data Systems	10.1108/IMDS-07-2015-0317
18	Saeed K.A., Abdinnour S., Lengnick-Hall M.L., Lengnick-Hall C.A.	Examining the Impact of Pre-Implementation Expectations on Post-Implementation Use of Enterprise Systems: A Longitudinal Study	2010	Decision Sciences	10.1111/j.1540-5915.2010.00285.x
19	Roxas B.	Effects of entrepreneurial knowledge on entrepreneurial intentions: A longitudinal study of selected South-east Asian business students	2014	Journal of Education and Work	10.1080/13639080.2012.760191
20	Jung D.I., Sosik J.J.	Effects of group characteristics on work group performance: A longitudinal investigation	1999	Group Dynamics	10.1037/1089-2699.3.4.279
21	Courty A., Godart N., Lalanne C., Berthoz S.	Alexithymia, a compounding factor for eating and social avoidance symptoms in anorexia nervosa	2015	Comprehensive Psychiatry	10.1016/j.comppsych.2014.09.011
22	Marjoribanks K.	Family background, social and academic capital, and adolescents' aspirations: A mediational analysis	1997	Social Psychology of Education	10.1023/A:1009602307141
23	Piyathasanan B., Mathies C., Patterson P.G., de Ruyter K.	Continued value creation in crowdsourcing from creative process engagement	2018	Journal of Services Marketing	10.1108/JSM-02-2017-0044
24	Gray D.M., D'Alessandro S., Johnson L.W., Carter L.	Inertia in services causes and consequences for switching	2017	Journal of Services Marketing	10.1108/JSM-12-2014-0408
25	Pai H.-C.	An integrated model for the effects of self-reflection and clinical experiential learning on clinical nursing performance in nursing students: A longitudinal study	2016	Nurse Education Today	10.1016/j.nedt.2016.07.011
26	Prati G., Albanesi C., Pietrantoni L.	The Reciprocal Relationship between Sense of Community and Social Well-Being: A Cross-Lagged Panel Analysis	2016	Social Indicators Research	10.1007/s11205-015-1012-8

Table A1. *Cont.*

No	Authors	Title	Year	Journal	DOI
27	Roemer E., Henseler J.	The dynamics of electric vehicle acceptance in corporate fleets: Evidence from Germany	2022	Technology in Society	10.1016/j.techsoc.2022.101938
28	Chaparro-Peláez J., Pereira-Rama A., Pascual-Miguel F.J.	Inter-organizational information systems adoption for service innovation in building sector	2014	Journal of Business Research	10.1016/j.jbusres.2013.11.026
29	Lauro N.C., Grassia M.G., Cataldo R.	Model-Based Composite Indicators: New Developments in Partial Least Squares-Path Modeling for the Building of Different Types of Composite Indicators	2018	Social Indicators Research	10.1007/s11205-016-1516-x
30	Zhu X., Wei Y., Lai Y., Li Y., Zhong S., Dai C.	Empirical analysis of the driving factors of China's 'Land finance' mechanism using soft budget constraint theory and the PLS-SEM model	2019	Sustainability (Switzerland)	10.3390/su11030742
31	Lee W.-K.	An elaboration likelihood model-based longitudinal analysis of attitude change during the process of IT acceptance via an education program	2012	Behaviour and Information Technology	10.1080/0144929X.2010.547219
32	Hallencreutz J., Parmler J.	Important drivers for customer satisfaction–from a product focus to image and service quality	2021	Total Quality Management and Business Excellence	10.1080/14783363.2019.1594756
33	Guo Z., Tan F.B., Turner T., Xu H.	Group norms, media preferences, and group meeting success: A longitudinal study	2010	Computers in Human Behavior	10.1016/j.chb.2010.01.001
34	Robina-Ramírez R., Medina Merodio J.A., McCallum S.	What role do emotions play in transforming students' environmental behavior at school?	2020	Journal of Cleaner Production	10.1016/j.jclepro.2020.120638

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