J-Icon : Jurnal Informatika dan Komputer
Vol. 13 No. 1, March 2025, pp. 45~50
DOI: 10.35508/jicon.v13i1.21007


# EVALUATION OF E-LEARNING SYSTEM INTEGRATION AT ABC UNIVERSITY

**Ratna Yulika Go[1*], Ary Prabowo[2], and Qori Halimatul Hidayah[3]**

**[1,2,3] Faculty of Computer Science, Universitas Esa Unggul, Jakarta, Indonesia 11440**
**Email[1*]: ratna.yulika@esaunggul.ac.id**
**Email[2]: ary.prabowo@esaunggul.ac.id**
**Email[3]: qori.halimatul@esaunggul.ac.id**

## ABSTRAK

Konsep *e-learning* sudah diadaptasi dan digunakan sejak tahun 1940-an di Indonesia. Perkembangannya terus mengalami kemajuan hingga saat ini. Adanya pandemi Covid-19 membuat penggunaan *e-learning* menjadi lebih komperhensif digunakan. Sayangnya Universitas ABC belum siap dengan perubahan yang drastis menjadi *full online* dan *e-learning* yang belum terintegrasi dengan Sistem Akademik (Siakad). Kendala lain yang hadapi adalah masih adanya *bug* sistem yang terjadi, kurang optimal forum diskusi. Sehingga pengguna yaitu mahasiswa dan dosen tidak menggunakan *e-learning* secara optimal. Untuk mengetahui akar masalah tersebut, penelitian ini dilakukan bertujuan mengetahui faktor pengaruh penggunaan *e-learning* pada Universitas ABC dengan hasilnya dapat memberikan rekomendasi bagi Universitas ABC untuk mengatasi kendala yang dihadapi. Metode yang digunakan yaitu metode kuantitatif untuk mengolah dan memvalidasi. Pendekatan yang digunakan yaitu UTAUT untuk mengetahui faktor-faktor yang mempengaruhi penggunaan *e-learning* dan dilakukan analisa menggunakan PLS SEM. Hasil penelitian yang didapatkan dari lima faktor yaitu PE, EE, SI, FC, dan BI terdapat satu faktor yang mempengauhi secara signifikan penggunaan *e-learning* yaitu SI. Sedangkan empat faktor lainnya tidak memberikan dampak signifikan. Rekomendasi dari penelitian ini adalah perlu adanya integrasi sistem *e-learning* dan Siakad agar *e-learning* dapat digunakan secara optimal, serta melakukan *maintenance* tiga bulan sekali, memfasilitasi akun *meeting* dan menambah fitur *audio video* pada forum diskusi.
Kata kunci: E-learning, UTAUT, PLS-SEM

## ABSTRACT

The concept of e-learning has been adapted and used in Indonesia since the 1940s, and its development has continued to progress to this day. The COVID-19 pandemic has led to more comprehensive use of e-learning. Unfortunately, ABC University was not prepared for the drastic shift to fully online learning, and its e-learning system is not yet integrated with the academic information system (SIAKAD). Other challenges include system bugs and a lack of optimization in discussion forums. As a result, students and lecturers are not able to use e-learning to its full potential. To identify the root causes of these issues, this study aims to determine the influencing factors of e-learning usage at ABC University, with the findings intended to provide recommendations for the university to address the challenges it faces. The study uses a quantitative method to process and validate the data. The UTAUT (Unified Theory of Acceptance and Use of Technology) approach is applied to identify the factors that affect e-learning usage, with analysis conducted using PLS SEM (Partial Least Squares Structural Equation Modeling). The study results show that among the five factors examined—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI)—only Social Influence (SI) significantly impacts e-learning usage, while the other four factors do not have a significant effect. The recommendations from this study include the need for system integration between e-learning and SIAKAD to ensure optimal use, as well as conducting maintenance every three months, facilitating meeting accounts, and adding audio-video features in discussion forums.
Keyword: E-learning, UTAUT, PLS-SEM

## 1. INTRODUCTION

E-learning in Indonesia has faced significant challenges, especially with the rapid transition to online learning following the COVID-19 pandemic. One of the main issues is the digital divide, where many rural and remote areas lack adequate internet infrastructure, leaving approximately 14% of villages without reliable internet access. This disparity in connectivity hampers students' ability to participate in online learning, particularly in regions where internet is both scarce and costly [1]. Additionally, device accessibility remains a barrier, with an estimated 30% of students lacking access to essential devices like

***) Corresponding Author**
Submitted : March 19, 2025
Accepted : April 8, 2025
Published : April 12, 2025

ISSN: 2337-7631 (Printed)
ISSN: 2654-4091 (Online)

computers or smartphones, which limits their engagement in online education. The shift has also exposed gaps in teacher preparedness, as over 60% of educators have expressed feeling unprepared to use digital teaching tools effectively, often defaulting to traditional, lecture-based approaches that reduce the interactivity of E-learning [2]. Furthermore, many students have reported that online learning content can be monotonous and challenging to understand, underscoring the need for more engaging and adaptive digital resources. Social isolation and stress are also on the rise, with 83% of students reporting feelings of loneliness due to reduced peer interaction, highlighting the psychological strain of prolonged E-learning. High internet data costs exacerbate these issues, especially for low-income families, and despite government subsidies, affordability remains a major concern for 68% of households. Additionally, outdated platforms and technical glitches further disrupt the learning process, as 57% of educational institutions face challenges with system integration and persistent bugs. Together, these issues illustrate the complex barriers to effective E-learning in Indonesia and the pressing need for targeted interventions to improve digital access, teacher training, and content quality [3].

The challenges facing in E-learning implementation in Indonesia have a direct impact on user behavior and behavioral intention, which are critical to the effective adoption and sustained use of digital learning platforms. The behavioral intention in E-learning contexts—defined by a user's readiness to engage with the system—is strongly influenced by external factors such as infrastructure, accessibility, and quality of content. When students and teachers face issues like limited internet access, inadequate devices, and monotonous content, their behavioral intention to use E-learning systems diminishes. For instance, with 30% of students lacking access to computers or smartphones, their likelihood of engaging with E-learning decreases, affecting both the frequency and depth of system usage. Similarly, teachers' lack of preparedness and digital literacy reduces their willingness to adapt their teaching methods, often resulting in a rigid, lecture-based approach that limits interactivity and engagement, which in turn dampens student intention to participate actively.

User behavior, or the actual engagement with E-learning, is further influenced by these systemic and technical barriers [4]. High data costs, technical glitches, and lack of integration with academic databases frustrate users, leading to lower usage consistency and satisfaction. In addition, social isolation and stress caused by minimal peer interaction affect students' motivation to log in and participate regularly, impacting overall user behavior and learning outcomes. Factors such as social influence, habit formation, and performance expectancy—which shape user behavior in E-learning contexts—are weakened in environments with limited infrastructure and poor content quality. As a result, addressing these issues is crucial not only for enhancing the effectiveness of E-learning platforms but also for fostering a positive behavioral intention and active, consistent user behavior among Indonesian students and teachers.

Previous research on behavioral intention and user behavior in E-learning highlights several critical factors influencing the adoption and sustained use of digital learning systems, particularly in contexts like Indonesia, where infrastructure and digital readiness vary significantly [5]. Studies utilizing frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) have demonstrated that performance expectancy, effort expectancy, social influence, and facilitating conditions are essential determinants of behavioral intention in technology use. For instance, research by [6] emphasizes the impact of social influence, particularly in collectivist cultures like Indonesia, where peer and instructor recommendations significantly affect students' willingness to engage with online platforms [7]. Additionally, habit formation plays a crucial role in continued usage behavior who found that consistent usage habits lead to sustained engagement with E-learning systems. However, challenges such as limited internet access and device availability hinder habit formation and active participation, as evidenced by a study from [8], which reported that unstable connectivity directly impacts learning outcomes. Furthermore, research by [2] highlights the importance of content quality in driving user satisfaction and continued use, revealing that engaging and relevant content increases students' behavioral intention to use E-learning platforms. Lastly, the psychological impact of E-learning, particularly feelings of isolation and stress reported by students during the pandemic, has been shown to affect retention and engagement, as noted in studies by [9]. Collectively, these findings underscore the need to address infrastructural, psychological, and cultural factors to improve E-learning effectiveness and foster positive user behavior in Indonesia's educational landscape [10].

This research identifies several critical research gaps in understanding E-learning acceptance and user behavior, particularly within the Indonesian context. First, while numerous global studies address E-learning adoption, there is a notable lack of focused research specific to Indonesian higher education institutions, especially at the micro level. This study aims to fill that void by examining the unique challenges and influencing factors at ABC University. Additionally, previous research did not conduct research to evaluate E-learning at ABC University. This research will help provide data and accuracy from lecturers and students who use the system. Finally, most existing studies provide a snapshot of user behavior at one point, leaving a gap for longitudinal analyses assessing changes in behavioral intention and user behavior over time. By addressing these gaps, the study seeks to contribute valuable insights for educational institutions, policymakers, and system developers aiming to enhance the effectiveness of digital learning platforms in Indonesia.

## 2. MATERIAL AND METHODS

**Research Design**

This study employs quantitative research methods to comprehensively analyse the factors influencing behavioral intention and user behavior in E-learning at ABC University. The quantitative component involves a survey to collect data on students' and lecturers' perceptions.

**Participants**

The population of this study is 75 lecturers and 222 students. The population consists of two faculties, namely the Faculty of Business Economics (Management and Accounting) and Design Engineering (Architecture, Visual Communication Design, Information Systems). Researcher used both faculties because Faculty of Business Economics and Design Engineering are the highest interest and lot of members than other faculty. Slovin’s method was used to calculated the sample of this research with the detail participants include total 62 lecturers and 174 students from ABC University. Participants were selected through stratified random sampling to ensure representation across various faculties and courses. The demographic characteristics of the respondents, such as age, gender, and field of study, were collected to analyse potential differences in perceptions and behaviors.

**Instruments**

Quantitative Survey is a structured questionnaire was developed based on the UTAUT model. The questionnaire utilized a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) for responses. The questionnaire includes items measuring key constructs, such as [11]:

- Performance Expectancy (PE): The perceived benefits of using the E-learning system.
- Effort Expectancy (EE): Uneven usage presents a problem in efforts to utilize e-learning.
- Social Influence (SI): The impact of peers and instructors on the users' intention to use E-learning.
- Facilitating Conditions (FC): Resources availability of and support necessary for effective E-learning.
- Behavioral Intention (BI): The readiness of users to engage with the E-learning system.
- Use Behavior (UB): UB highlights the behavior of using e-learning, including activities like installing, using, maintaining, and updating.

**Data Collection**

Data collection occurred over four weeks. The survey was distributed online via the university's communication channels, and participants were encouraged to complete it voluntarily. Interviews were conducted using video conferencing tools to accommodate participants' availability and ensure accessibility.

**Data Analysis**

The data collected from the surveys were analysed using Partial Least Square Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 software. This analysis allowed for the assessment of the relationships among the various constructs, identifying significant predictors of behavioral intention and user behavior.

The questionnaire data that has been distributed and filled out by respondents will be collected and tested against the hypotheses outlined using Structural Equation Modelling (SEM). This process is conducted to evaluate the extent to which the proposed conceptual framework aligns with the data. The results from the questionnaire will be mapped on a Likert scale with the assistance of Microsoft Excel and then imported into the data analysis tool, SmartPLS 4.0. The results of the quantitative data processing will be followed by hypothesis testing.

Structural Equation Modeling (SEM) is a statistical method used to examine the relationships between variables and indicators with other variables. SEM can analyze various different variables, and measurement errors can be observed and tested with criterion variables [12]. The SEM algorithm can solve equations in n-dimensional space and estimate model parameters [13]. SEM analysis has advantages such as examining major components, investigating factors, and conducting discriminant analysis or multiple regression. This is due to the flexibility inherent in SEM, which allows for defining relationships between predictive variables and criteria, constructing latent variables that cannot be directly observed, addressing measurement errors in observed variables, and replicating analyses into a matrix format and information, thus creating a specific model for research [14].


ISSN: 2337-7631 (Printed)
ISSN: 2654-4091 (Online)

 

**UTAUT Hypotheses**

Table 1 shows the hypotheses commonly derived from the UTAUT model.

Table 1. Research hypotheses

| Hypotheses | Notes |
|---|---|
| H1: Performance Expectancy (PE) positively influences Behavioral Intention (BI) | This hypothesis suggests that the expectation of better performance from using e-learning will positively affect the intention to use it. |
| H2: Effort Expectancy (EE) positively influences Behavioral Intention (BI) | This hypothesis proposes that the ease of using e-learning will positively affect the intention to use it. |
| H3: Social Influence (SI) positively influences Behavioral Intention (BI) | This hypothesis indicates that social factors, such as influence from friends, relatives, and lecturers, will positively affect the intention to use e-learning |
| H4: Facilitating Condition (FC) positively influences Behavioral Intention (BI) | This hypothesis posits that the availability of resources and support will positively affect the intention to use e-learning |
| H5: Behavioral Intention (BI) positively influences Use Behavior (UB) | This hypothesis suggests that a strong intention to use e-learning will positively affect its actual use. |

## 3. RESULTS AND DISCUSSION

**Descriptive Statistics of Respondents**

A total of 174 students and 62 lecturers completed the distributed questionnaires but the data need to be cleaned before used. The data is then filtered with the provision that if there is duplication, pattern and asymmetry then it is removed. After the data cleaning process, 55 lecturer data and 146 student data were obtained which were used in the analysis of this study.

The findings reveal that participants represented five different study programs, with the Management program accounting for the largest share at 38%. The questionnaire responses were predominantly from male students, numbering 89 (61%). Most respondents fell within the age range of 31-40 years, comprising 54 individuals (37%). Additionally, the respondents reported their usage duration of the E-learning system, with the average user having engaged with the system for 2-3 years and possessing adequate internet access. The results obtained based on five study programs, namely Management lecturers with the largest population of 36%. The filling of this questionnaire was dominated by women as many as 33 people or 60%. The age range of lecturers at ABC College in this study was 31-40 years and 41-50 years, namely 15 people (27%) each. In addition to the personal data filled in, lecturers also filled in the length of time they used the E-learning system. On average, lecturers who have used the E-learning system for 2-3 years with adequate internet access.

**Measurement Model Evaluation**

The measurement model evaluation was conducted using the PLS algorithm. According to the established criteria, variables with values below 0.7 were excluded from the model. Five variables did not meet this criterion: PE4, FC1, FC2. In the lecturer's measurement model, an additional five variables—PE4, FC1, FC2, FC3 also failed to meet the threshold. After these variables were removed, the outer loading values for the remaining variables were above 0.7, satisfying the required criteria.

Following this, the Average Variance Extracted (AVE) test was performed. The AVE test assesses how well indicator variables represent their intended constructs. For AVE validity, a value of 0.5 or higher is required, indicating that the indicator variables explain at least 50% of the variance of the measured construct. An AVE value below 0.5 suggests that the variable does not adequately represent the construct and is therefore considered invalid. The AVE test results are presented in Table 2.

Table 2. Test results of AVE

| Variable | Value of AVE Student | Value of AVE Lecturer | Notes |
|---|---|---|---|
| *Performance Expectancy* | 0,756 | 0,762 | Valid |
| *Effort Expectancy* | 0,830 | 0,796 | Valid |
| *Facilitating Condition* | 0,745 | - | Valid |
| *Behavioral Intention* | 0,832 | 0,856 | Valid |
| *User Behaviour* | 0,830 | - | Valid |

The results shown in Table 2 indicate that the AVE values exceed the 0.5 threshold, categorizing them as valid. The Social Influence (SI) variable, with an outer loading value of 1.000, was automatically deemed valid by the SmartPLS 4.0 system, so it was not displayed. Additionally, the highest AVE value among students was for the Behavioral Intention (BI) variable at 0.832, while the lowest AVE values for students


ISSN: 2337-7631 (Printed)
ISSN: 2654-4091 (Online)

 

were for FC the at 0.745. Among lecturers, the highest AVE was for the BI variable at 0.856, and the lowest was for the PE variable at 0.762.

**Discriminant and Reliability Test**

The discriminant validity test reveals that the values for the BI1 and BI2 variables among students are 0.896 and 0.928, respectively, surpassing the indicator values for BI1 and BI2 across other variables. This pattern holds for other variables, with each having indicator values greater than those of unrelated indicators. Consequently, all indicator values can be considered valid, passing the discriminant validity test.

Following this, a reliability test using Composite Reliability (CR) was conducted. CR values above the threshold of 0.7 indicate strong reliability. The results confirm that all CR values for each variable exceed this threshold, with the highest CR value for students being 0.936 for the Effort Expectancy (EE) variable. This finding demonstrates that all CR values meet or exceed the established reliability standard, showing consistent measurement of the same construct by each indicator.

**Structural Model Evaluation**

The structural model in Structural Equation Modeling (SEM) is evaluated for validity and model fit by testing R-square, effect size (f2), and significance. The R-square test results indicate that, for students, the dependent constructs Behavioral Intention (BI) and User Behavior (UB) have values of 0.605 (60.5%) and 0.74 (74%), respectively. These moderate R-square values suggest that the predictor variables in the model can explain a substantial portion of the variance in the dependent variables.

**Effect Size (f2) and Significance Test**

The f2 test results classify the effect sizes of exogenous variables on endogenous variables into two large categories, three medium categories, and four small categories. In the large category, the Habit variable has an effect of 0.400 on the UB variable, while BI has an effect size of 0.437 on UB, indicating significant contributions of these predictor variables in explaining variations in the dependent variables.

A significance test using bootstrapping (with a sample size of 5000, two-tailed test type, and 0.05 significance level) showed two significant variable influence and three that was not significant. The Social Influence (SI) variables significantly affect the BI variable, while BI significantly impact the UB variable. However, the variables Effort Expectancy (EE), Facilitating Conditions (FC), Performance Expectancy (PE), do not significantly affect BI, as their p-values exceed 0.05 or t-statistics fall below 1.96.

**Hypothesis Testing**

Following the evaluation of both the outer and inner models, hypothesis testing was performed, primarily focusing on assessing structural model relationships. Structural Equation Modeling using Partial Least Squares (PLS-SEM) prioritizes the examination of relationships between constructs rather than individual variables. The hypothesis test results for students and lecturer showed that one out of the five hypotheses were supported: H3. However, hypotheses H1, H2, H4 and H5 were not supported, as they did not demonstrate a significant impact on the endogenous variables.

**Final Research Model**

After the evaluation of the measurement and structural models, hypothesis testing, and discussions, the final research model was established. Figure 1 presents the refined model based on the cumulative findings from these analyses.

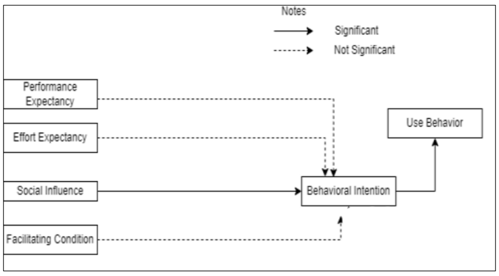


Figure 1. Final research model

**Recommendations**

This study identified three primary variables—habit, social influence, and behavioral intention—that significantly influence students' intention to utilize the E-learning system at ABC University. To improve system adoption, targeted recommendations were developed. For students, promoting online social spaces, establishing consistent study routines, and using the system for accessing lecture materials are encouraged. ABC University is recommended to organize regular orientation sessions, provide technical training, integrate the E-learning system with video conferencing tools, and increase server and storage capacity. For system developers, simplifying the system, adding features for achievement sharing, and offering


ISSN: 2337-7631 (Printed)
ISSN: 2654-4091 (Online)

comprehensive technical support through regular maintenance are essential steps. That to enhance system effectiveness and acceptance, fostering a more interactive and efficient learning environment.

## 4. CONCLUSION AND SUGGESTION

This study sought to identify the factors that affect student acceptance of the E-learning system at ABC University, focusing on active students and lecturer in educational activities. Through problem identification, literature review, data collection, and data analysis, this research highlighted that social influence is the key factor impacting user acceptance. Social influence significantly affect behavioral intention to adopt the system, which in turn positively influences actual user behavior.

Based on these findings, five key recommendations were proposed, targeting four main stakeholder groups and arranged by priority to positively impact user experience and aid institutional decision-making. However, limitations in this study may affect the results. The short timeframe for questionnaire distribution might have restricted data diversity. Future studies should extend data collection periods for more comprehensive insights. Moreover, the limited variation in secondary data, particularly user activity logs, made it challenging to accurately gauge system usage rates. Future research should aim for more detailed activity logs to better assess user engagement.

## REFERENCES

[1] P. V. Nguyen, “Improving The Effectiveness of E-Learning Based on The Impact of The Technology Solution,” *Int. Conf. Educ. e-Learning Innov.*, vol. 9, no. 66 2, pp. 1–4, 2012, doi: 10.1109/ICEELI.2012.6360640.

[2] D. Al-Fraihat, M. Joy, R. Masa’deh, and J. Sinclair, “Evaluating E-learning systems success: An empirical study,” *Comput. Human Behav.*, vol. 102, pp. 67–86, 2020, doi: 10.1016/j.chb.2019.08.004.

[3] Badan Pusat Statistik, “Potret Pendidikan Indonesia Statistik Pendidikan Indonesia 2018,” *Badan Pus. Stat.*, 2018, [Online]. Available: https://www.bps.go.id/publication/2018/12/06/a65b526c119ce8f799e5ea63/statistik-pendidikan-2018.html.

[4] D. Napitupulu, “e-Government Maturity Model Based on Systematic Review and Meta-Ethnography Approach,” *J. Bina Praja*, vol. 8, no. 2, pp. 263–275, 2016, doi: 10.21787/jbp.08.2016.263-275.

[5] S. S. Utami and N. Aini, “Pemanfaatan E-Commerce Dalam Upaya Meningkatkan Penjualan Produk Handycraft Mama Art Deco,” *Interv. Komunitas*, vol. 1, no. 1, pp. 22–33, 2019, [Online]. Available: https://ojs.itb-ad.ac.id/index.php/IK/article/view/240.

[6] A. Tarhini, P. Balozain, and F. J. Srour, “Emergency management system design for accurate data: a cognitive analytics management approach,” *J. Enterp. Inf. Manag.*, vol. 34, no. 2, pp. 697–717, 2021, doi: 10.1108/JEIM-11-2019-0366.

[7] E. D. Wagner, “Enabling Mobile Learning,” *Educ. Rev.*, vol. 40, no. 3, pp. 41–42, 2005. [Online]. Available: https://www.learntechlib.org/p/99141/?nl=1.

[8] S. Sfenrianto, E. Tantrisna, H. Akbar, and W. Mochamad, “E-learning effectiveness analysis in developing countries: East nusa tenggara, Indonesia perspective,” *Bull. Electr. Eng. Informatics*, vol. 7, no. 3, pp. 417–424, 2018, doi: 10.11591/eei.v7i3.849.

[9] O. Saidani Neffati *et al.*, “An educational tool for enhanced mobile e-Learning for technical higher education using mobile devices for augmented reality,” *Microprocess. Microsyst.*, vol. 83, 2021, doi: 10.1016/j.micpro.2021.104030.

[10] J. S. Asgarpoor, “Asynchronous course design 101,” *2019 Int. Annu. Conf. Proc. Am. Soc. Eng. Manag. 40th Meet. Celebr. A Syst. Approach to Eng. Manag. Solut. ASEM 2019*, 2019, doi: https://www.proquest.com/openview/17f52b42338867ebb3e87ae37890990e/1?cbl=2037614&pq-origsite=gscholar.

[11] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” *MIS Q. Manag. Inf. Syst.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.

[12] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt. *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage Publications Inc, Thousand Oaks, CA, 2017.

[13] H. W. Willaby, D. S. J. Costa, B. D. Burns, C. MacCann, and R. D. Roberts, “Testing Complex Models With Small Sample Sizes : A Historical Overview And Empirical Demonstration Of What Partial Least Squares (PLS) Can Offer Differential Psychology,” *Pers. Individ. Dif.*, vol. 84, pp. 73–78, 2015, doi: 10.1016/j.paid.2014.09.008.

[14] W. W. Chin, “The Partial Least Squares Approach For Structural Equation Modeling,” *Mod. methods Bus. Res.*, no. April, pp. 295–336, 1998.