Journal of Business Research 154 (2023) 113328

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

A review of exploratory factor analysis in tourism and hospitality research: Identifying current practices and avenues for improvement

Matt C. Howard *, Jennifer Henderson

The University of South Alabama, Mitchell College of Business, United States

A B S T R A C T

We perform a literature review of exploratory factor analysis (EFA) in six premier tourism and hospitality journals to (1) identify best practices, (2) ensure that researchers apply these best practices, and (3) enable future authors to be more precise in their reporting of EFA. Our results identify that researchers (1) frequently obtain large sample sizes and perform data quality checks, (2) overwhelmingly prefer the principal component approach rather than the common factor approach, (3) are reliant on varimax and other orthogonal rotations, (4) utilize the Kaiser criterion rather than more supported approaches, (5) produce large primary and secondary loadings, and (6) have never identified concerning common method variance via Harman's one-factor test. We urge researchers to utilize oblique rotations and supported factor retention approaches, and we recommend that researchers should place more attention on their secondary loadings. We lastly call for a moratorium on Harman's one-factor test.

1. Introduction

Researchers of tourism and hospitality regularly aggregate scores from multiple indicators to represent latent constructs, which can be most frequently seen in the application of multiple-item scales. To provide assurances that these indicators represent a common underlying construct, these researchers often perform exploratory factor analysis (EFA). EFA identifies the underlying structure regarding a set of indicators by identifying emergent latent factors as well as the extent that each indicator relates to each latent factor (Cudeck, 2000; Hair et al., 2018; Fabrigar & Wegener, 2011). Further, indicators for separate posited constructs should not be primarily represented by a single latent factor, as such an occurrence would indicate that common method variance unduly inflated observed relations. Researchers of tourism and hospitality again use EFA to perform Harman's one-factor test, which provides an assessment of this possibility (Chang et al., 2010; Fuller et al., 2016; Podsakoff et al., 2003). It cannot eliminate the influence of common method variance, but it is intended to indicate the extent that common method variance may be a concern. Therefore, EFA is a powerful tool that is regularly applied in the study of tourism and hospitality to assess the latent structure of a set of indicators.

Despite its popularity, no focused review exists regarding the application of EFA in tourism and hospitality research, although such reviews are relatively common in other domains of study (Beavers et al., 2013; Roberson et al., 2014; Watkins, 2018). Such periodic reviews are necessary for three primary reasons. First, although prior authors have suggested best-practices for EFA, there is no guarantee that researchers are following these best-practices. Prior reviews of EFA in other domains have regularly discovered that researchers fail to apply commonly suggested guidelines, and they often fail to report their analytical approaches altogether (Conway & Huffcutt, 2003; Howard, 2016; Reio & Shuck, 2015). Second, best-practices for EFA are frequently changing as authors continuously make discoveries; however, there is no guarantee that researchers are adopting these new best practices, and the use of EFA in tourism and hospitality may be built on outdated recommendations. Third, many guidelines for EFA are based on relatively arbitrary criteria. For instance, most authors interpret the strength of factor loadings based on absolute values (e.g., 0.40, 0.50, and 0.60), but absolute value cutoffs often do not relate to firm statistical justifications. A review of EFA in tourism and hospitality research could enable future authors to be more precise in the interpretation and reporting of their results relative to prior research. Researchers, for example, could report the strength of their factor loadings and cutoffs using percentiles that are relative to the study of tourism and hospitality, such that the strength of their effects could be interpreted in comparison to prior research in the associated domain of study. Interpretations could be more straightforward, and researchers could have greater assurances regarding the validity of their conclusions.

Given these potentially powerful implications, the current article performs a literature review of EFA practices in research on tourism and hospitality. We begin by reviewing the steps and required decisions when conducting an EFA to investigate the factor structure of measures,

* Corresponding author at: 5811 USA Drive S., Rm. 337, Mitchell College of Business, University of South Alabama, Mobile, AL 36688, United States.
E-mail address: MHoward@SouthAlabama.edu (M.C. Howard).

https://doi.org/10.1016/j.jbusres.2022.113328
Received 10 April 2021; Received in revised form 9 September 2022; Accepted 15 September 2022

followed by a brief review of Harman's one-factor test. During this review, we identify research questions regarding the use and reporting of EFA in tourism and hospitality, such as the frequency of reported sample sizes, factor loading cutoffs, and factor loadings themselves. We also note that the current review spans several decades of research, allowing us to assess the relation of publication year with the various aspects of EFA. Doing so enables insights into whether and how EFA practices are evolving over time – for better or worse. Then, the current article provides a review of the current literature, wherein the reporting of EFA in tourism and hospitality is quantified and inferences are made about the appropriateness of the applied approaches. Lastly, the current article discusses the implications of our numerical results, and recommendations are made regarding modern applications of EFA. We suggest immediate solutions for curbing problematic uses of EFA, but we also highlight recent statistical developments to shape future applications. From these efforts, the current article reviews the use of EFA to provide immediate and future benefits for the study of tourism and hospitality.

It should also be noted that the current review provides implications beyond tourism and hospitality. Research on tourism and hospitality is inherently interdisciplinary, and its representative studies overlap with marketing, management, human resources (HR), psychology, management information systems (MIS), human–computer interaction (HCI), economics, supply chain management, and many other fields of study. This is reflected in the applied scales to measure commonly studied constructs in tourism and hospitality, such as destination image, place attachment (marketing), job satisfaction, employee performance (management/HR), resident perceptions of tourism (psychology), intentions to use technologies (MIS/HCI), and other examples pervasive in the literature. By performing a review of EFA in tourism and hospitality, the current article also provides insights into the use of EFA in studies relevant to these other fields. To leverage this benefit, we also code our collected sources based on their overlapping field of study and provide separate results for each representative domain. Readers interested in specific subsets of tourism and hospitality research – or even alternative fields altogether – can refer to these results to understand the current state of EFA in their specific domains. Therefore, the current article provides broad benefits to all domains of tourism and hospitality research as well as even research outside of tourism and hospitality.

2. Background

EFA is currently applied in tourism and hospitality research for two purposes: factor structure investigations and Harman's one-factor test. We separately review both in the current article, beginning with factor structure investigations and followed by Harman's one-factor test.

2.1. Factor structure investigations

When investigating factor structures, the purpose of EFA is to identify a set of underling factors that adequately explain the covariance in the studied indicators, and many numerical results are provided for researchers to determine how well their factor structures achieve this goal (Costello & Osborne, 2005). For instance, EFA results indicate the extent of total variance that all emergent factors explain in all indicators together, and it also indicates the extent that each factor explains the variance in each specific indicator. Identifying emergent factors provides assurances to researchers that they can aggregate their indicators for more manageable analyses (i.e., data reduction), as they can have confidence that their indicators assess an underlying construct. As further discussed in our discussion section, researchers often replicate the results of their EFA with confirmatory factor analysis (CFA) using an alternative sample, and they should also strive to obtain validity information regarding their measures (e.g., convergent, concurrent, and discriminant validity). While EFA can provide support for the aggregation of indicators, validity evidence is needed to support that these aggregated indicators assess their intended construct (Clark & Watson, 1995; Hinkin, 1995, 1998; Miller & Simmering, 2022).

To perform an EFA for investigating factor structures, researchers must complete five steps that involve several analytical decisions: (1) data assessment, (2) factor extraction, (3) factor retention, (4) factor rotation, and (5) indicator assessment (Conway & Huffcutt, 2003; Howard, 2016; Reio & Shuck, 2015; Watkins, 2018). We review each of these five steps below, and we discuss the analytical decisions that must be made for each step.

2.1.1. Step 1: Data assessment

Before conducting EFA, researchers must confirm that their data is suitable, which includes ensuring that the obtained sample size is sufficient for EFA. Many recommendations exist for minimum sample sizes, which are based on absolute values, the number of indicators, as well as the number of indicators and anticipated factors (Gaskin & Happell, 2014; Hogarty et al., 2005; Reio & Shuck, 2015; Yong & Pearce, 2013). Regarding absolute values, earlier authors recommended that 100 or 200 participants are necessary to obtain accurate EFA results, but more recent authors have argued that these sample sizes are likely insufficient for typical factor analytic approaches (Howard, 2016; Rouquette & Falissard, 2011; Watkins, 2018).[1] These authors instead recommended 300 or even 400 participants. Regarding the number of indicators, earlier authors suggested that 5 or 10 participants are required for each indicator; however, recent authors recommend that 5 participants per indicator is too few, and 10 or even 20 participants per indicator is necessary (Beavers et al., 2013; Osborne et al., 2014). Lastly, the number of indicators and anticipated factors is the most difficult to estimate, but it is likely the most accurate approach for determining sample size. The required sample size for accurate EFA estimates is based, in part, on the indicators' covariances (e.g., communalities), and the number of indicators and anticipated factors is among the few methods to estimate indicator covariance before data is collected (Hair et al., 2018). No formula exists to provide estimates based on indicators and anticipated factors, but authors have provided tables created from simulations (Gaskin & Happell, 2014; Rouquette & Falissard, 2011). Researchers can use these tables based on their study parameters to estimate their required sample size, akin to statistical power tables.

Together, modern researchers recommend larger absolute (e.g., >300) and ratio (e.g., >10 participants per indicator) guidelines for EFA than older recommendations, but no universal guideline exists for the necessary sample size. For this reason, we review prior studies to assess their sample sizes, sample sizes relative to number of indicators, as well as sample sizes relative to number of indicators and obtained factors. By doing so, we can provide researchers of tourism and hospitality a better frame-of-reference for expected sample sizes in conducting EFA.

Research Question 1: What sample sizes are used for EFA in tourism and hospitality research?

In addition to the quantity of data, researchers must ensure that the quality of their data is sufficient for EFA. EFA is susceptible to many of the same data concerns as other statistical analyses. Researchers must ensure that their participants provide accurate responses (e.g., using attention checks; Meade & Craig, 2012), and they should use typical approaches for handling missing data (Newman, 2014), outliers (Aguinis et al., 2013), and other similar concerns (Hair et al., 2018; Ritchie et al., 2005). While some approaches to EFA may be resilient to certain aspects of poor data quality (noted below), it is the onus of the researcher to ensure that their chosen approaches are not vulnerable to these typical data concerns.

One aspect of data quality, however, is relatively specific to factor

[1] Small sample sizes (e.g., 50) can be suitable for EFA given certain data qualities and/or specialized analyses, but these situations are atypical in the broader context of EFA.

analysis: ensuring that indicators possess sufficient covariance (Dziuban & Shirkey, 1974; Howard, 2016; Kaiser, 1970, 1974; Tobias & Carlson, 1969). EFA provides few implications if performed on a set of largely unrelated indicators; although authors could obtain factor structures that appear normal, they would explain little underlying variance. Two analyses are typically used to investigate this concern, Bartlett's test of sphericity (Bartlett, 1951) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1974). Bartlett's test assesses whether the observed correlation matrix is significantly different from an identity matrix, which would be a correlation matrix of indicators with absolutely no interrelation (Tobias & Carlson, 1969). If Bartlett's test is statistically significant, then the indicators can be considered to possess sufficient covariance to conduct EFA. Alternatively, the KMO test indicates the extent of underlying variance in indicators that can be attributed to unobserved latent factors, and it is interpreted on ranges of values (Hair et al., 2018). Based on Kaiser's (1974) recommendations, values from 0.00 to 0.50 are unacceptable, 0.50–0.60 are miserable, 0.60–0.70 are mediocre, 0.70–0.80 are middling, 0.80–0.90 are meritorious, and 0.90–1.00 are marvelous. In other words, values below 0.60 indicate that factor analysis is likely unsuitable, whereas values above 0.60 indicate that factor analysis is likely suitable. Because Bartlett's test and the KMO test are two valuable data quality assessments specific to factor analysis, we review the frequency of their use.

Research Question 2: How frequently are Bartlett's test and the KMO test applied in tourism and hospitality research?

2.1.2. Step 2: Factor extraction

After the researcher has ensured that their data is suitable for EFA, they must make their analytical decisions regarding the EFA itself. The first of these is the factor extraction method. While many factor extraction methods exist, the two most discussed are principal components analysis (PCA) and principal axis factoring (PAF) (Beavers et al., 2013; Howard, 2016; Watkins, 2018). Tourism and hospitality researchers do not appear to debate their merits as vigorously as other research domains (Jain & Shandliya, 2013; Preacher & MacCallum, 2003), but it is nevertheless important to establish and understand their differences.

PCA is often used when the objective is to summarize the model's original variance into a minimum number of factors for prediction purposes. This approach is taken when data reduction is the primary aim of the researcher, as PCA focuses on identifying the minimum number of factors needed to account for maximum total variance represented by the original variables (Hair et al., 2018). Data reduction does not attempt to model the structure of covariance among the original variables (Fabrigar et al., 1999), instead focusing on maximizing explained variance within the measured variables. Additionally, PCA does not discriminate between shared and unique variance (Costello & Osborne, 2005), and as such, the resulting components represent both common and unique variance. This approach is preferred when the researcher has prior knowledge that the specific and error variance represent only a small portion of total variance (Hair et al., 2018). Although PCA has been classified as a data reduction method as opposed to a true method of factor analysis, it remains the default extraction method in statistical programs such as SPSS and is frequently regarded as the most popular method of extraction in EFA (Costello & Osborne, 2005; Howard, 2016; Watkins, 2018).

Alternatively, PAF is used to identify underlying factors or dimensions that best account for shared variance among indicators (Hair et al., 2018). Unlike PCA, PAF only considers the common or shared variance, with resulting factors being derived from common variance alone. This approach does not assume that the indicators possess multivariate normality, and as a result, is able to provide accurate results in most situations (Costello & Osborne, 2005). Unlike PCA's primary goal of data reduction, PAF is aimed at producing factor loading estimates that best explain the observed correlation matrix (De Winter & Dodou, 2012). This approach is favorable when the researcher does not possess prior knowledge of specific and error variance and prefers to eliminate this variance from the solution (Hair et al., 2018). PAF is often touted as being more theoretically-sound than other extraction methods and has demonstrated an ability to provide accurate results in a wide number of situations (Howard, 2016).

Given the differences in these approaches, it is necessary to review their frequency of application in tourism and hospitality research to determine whether the field is reliant on the principal component model, the common factor model, or something else entirely.

Research Question 3: How frequently are PCA and PAF applied in tourism and hospitality research?

2.1.3. Step 3: Factor retention

Next, researchers must determine their approach for identifying factors that explain a meaningful amount of variance in their indicators. Most of these approaches are based on eigenvalues, which are the summation of all indicator factor loadings respective to that factor (Brown, 2001; Larsen & Warne, 2010; Ledesma & Valero-Mora, 2007). Because factor loadings indicate the extent that a factor accounts for the variance in an indicator, eigenvalues are a numerical representation of the variance that a factor accounts in all indicators together. Researchers seek to retain factors with large eigenvalues due to their explanatory power, and they also remove factors with small eigenvalues due to their general irrelevance. Researchers must also assess whether the retained factors adhere to their a priori theoretical perspective(s), and they may select the most theoretically appropriate factor structure when retaining multiple different factor solutions can be empirically justified based on eigenvalues. It is therefore imperative for researchers to determine qualifications for large and small eigenvalues.

The most common factor retention approach has historically been the Kaiser criterion (i.e., latent root) (Howard, 2016; Watkins, 2018). The Kaiser criterion specifies that researchers should retain all factors with an eigenvalue greater than 1. Each indicator contributes a value of 1 to the eigenvalues, and therefore a factor with an eigenvalue greater than 1 explains more variance than a single indicator alone (Hair et al., 2018). Despite its popularity, the Kaiser criterion is among the least effective approaches to make factor retention decisions. A multitude of studies have demonstrated that the Kaiser criterion routinely overestimates the number of factors to retain, and many authors have strongly recommended that researchers stop applying the Kaiser criterion (Braeken & Van Assen, 2017; Courtney & Gordon, 2013; Patil et al., 2008).

Alternatively, the visual scree plot analysis is likewise a popular factor retention approach (Hair et al., 2018; Howard, 2016; Watkins, 2018). To perform a scree plot analysis, the researcher sequentially plots their eigenvalues on a chart from largest to smallest. They then visually observe where the last "elbow" occurs, which is where the last reduction in eigenvalue size occurs that is noticeably larger than the others. For instance, in the following sequence of eigenvalues, [5.00, 4.00, 1.00, 0.90, 0.80], the elbow occurs after the second eigenvalue, indicating that the researcher should interpret a two-factor solution. While scree plot analyses have been supported as an effective approach to factor retention decisions (Laher, 2010; Roberson et al., 2014), some researchers are skeptical of their subjective nature. Indeed, there is no guarantee that a researcher can correctly identify an elbow, and the decision may be ambiguous in certain cases. These concerns are amplified if researchers do not report their eigenvalues in full. Therefore, authors have called for the application of more objective approaches that can produce more clear-cut factor retention decisions.

Among the most widely supported factor retention methods is parallel analysis (Garrido et al., 2013; Green et al., 2015; Hayton et al., 2004; Lim & Jahng, 2019). In conducting a parallel analysis, the researcher creates a number of datasets (e.g., 10,000) composed entirely of random values with the same number of indicators and observations as the EFA dataset. The researcher then calculates eigenvalues for each of these random value datasets, and they compare the eigenvalues from their EFA to the 95th percentile of the eigenvalues from the random value datasets. If the EFA eigenvalue is larger than its respective 95th percentile eigenvalue, then the factor should be retained as it explains more in the indicators than random variance alone. Modern computer programs can create datasets of random values in an automated manner, and parallel analysis can now be performed with relative ease. Despite its ease and accuracy, parallel analyses are relatively uncommon in the social sciences, appearing much less frequently than Kaiser's criterion and scree plot analyses (Costello & Osborne, 2005; Watkins, 2018).

Given these considerations, we assess the frequency of these factor retention approaches. While it would be desirable for tourism and hospitality research to apply more accurate approaches, such as parallel analysis, this cannot be assumed. Therefore, identifying a potential limitation in the current literature could provide large implications for future research.

Research Question 4: How frequently are various factor retention methods applied in tourism and hospitality research?

2.1.4. Step 4: Factor rotation

After determining the number of factors to retain, researchers must also specify their factor rotation method. Factor rotation methods alter the initial factor loadings to be equally accurate but more interpretable. While an unlimited number of factor rotations can be created, they are all classified into two categories: orthogonal and oblique (Hair et al., 2018).

Orthogonal rotations force the emergent factors to be uncorrelated, and many authors have strongly criticized this aspect of orthogonal rotations (Harman, 1976; Howard, 2016; Osborne, 2015). All factors are correlated to some extent – even if an extremely small extent. Some prior authors have argued that orthogonal rotations are appropriate if the correlations of emergent factors are small (e.g., <0.33; Corner, 2009), but it is unusual for researchers to ignore relevant variance that can be easily modeled. For this reason, prior reviews of EFA have called for researchers to strongly reconsider the use of orthogonal rotations. Of these rotations, however, varimax is likely the most popular (Sass & Schmitt, 2010; Watkins, 2018). Varimax seeks to increase the variance in factor loadings, such that small values are closer to 0 and large values are closer to 1 (Corner, 2009; Darton, 1980; Hair et al., 2018). By doing so, factor structures become more interpretable, as small values become more differentiated from large values and indicators can be more easily matched to their respective factors.

Alternatively, oblique rotations allow emergent factors to be correlated, and they do not change the size of correlations between latent factors; factors that are strongly correlated remain strongly correlated, and factors that are weakly correlated remain weakly correlated (Costello & Osborne, 2005; Harman, 1976). Critics of orthogonal rotations have called for researchers to exclusively apply oblique rotations (Howard, 2016; Osborne, 2015). The most popular oblique rotation is likely oblimin (Sass & Schmitt, 2010; Watkins, 2018). Oblimin often produces factor loadings similar to the varimax rotation but are oblique, which is perhaps a contributing factor to its popularity (Darton, 1980). The rotation method seeks to minimize the loading of indicators onto multiple factors, such that indicators are more likely to clearly relate to a single factor. Thus, oblimin rotation both allows factors to correlate and provides interpretable solutions.

While many other rotations exist, we do not review them due to their relative dearth of popularity. It is expected that most researchers of tourism and hospitality either apply varimax or oblimin rotations, but we also assess the extent that other rotations are applied.

Research Question 5: How frequently are various factor rotation methods applied in tourism and hospitality research?

2.1.5. Step 5: Indicator assessment

A primary goal of EFA is to reduce a set of indicators into a smaller, more interpretable set of factors. In doing so, researchers must determine which indicators are and are not representative of emergent factors. Factor loadings are used to make such decisions, which are numerical representations of the variance that a factor explains in an indicator. Like the prior steps, many guidelines have been proposed for interpreting factor loadings, which are based on primary loadings, cross-loadings, and the difference between primary and cross-loadings.

Primary loadings refer to the factor loadings of indicators on their posited construct and/or the construct for which they have the strongest factor loadings. Researchers want their indicators to be representative of their posited factors, and therefore indicators are frequently removed from analyses if their primary loadings are less than 0.40, 0.50, or even 0.70 (Gaskin & Happell, 2014; Reio & Shuck, 2015; Yong & Pearce, 2013). Alternatively, cross-loadings refer to the factor loadings of indicators on their non-posited constructs and/or the constructs for which they do not have the strongest factor loadings. Cross-loading indicators can inflate observed relations between variables, and therefore it is desirable to remove indicators with strong cross-loadings from analyses. Researchers often remove indicators with cross-loadings larger than 0.30, 0.40, or 0.50 (Rouquette & Falissard, 2011; Watkins, 2018). Lastly, authors have suggested that cross-loadings should be assessed in a manner relative to primary loadings. That is, the strength of an indicator's cross-loading should be compared to the strength of that indicator's primary loading to determine whether the cross-loading is large enough to be concerning. To do so, researchers have proposed cutoffs for the difference between the indicator's smallest primary loading and its strongest cross-loading, such as 0.20 (Howard, 2016).

Together, a wide spectrum of cutoffs exists for primary loadings, cross-loadings, and their difference, illustrating a clear need to review the literature and determine which cutoffs are being applied. Such a review could provide guidance for future researchers in tourism and hospitality towards the appropriate factor loading cutoffs to use for their own EFAs.

Research Question 6: What cutoffs are commonly applied for primary loadings, cross-loadings, and the difference between primary and cross-loadings in tourism and hospitality research?

It should be recognized, however, that the size of retained factor loadings may not match the size of stated cutoffs, and some authors may not state their cutoffs entirely. It is important to evaluate the size of factor loadings for retained indicators. We assess the smallest primary loadings, the largest cross-loadings, and their smallest difference reported in prior articles.

Research Question 7: What are the smallest primary loadings, largest cross-loadings, and smallest difference between primary and cross-loadings reported in tourism and hospitality research?

2.2. Harman's One-Factor tests

Common method variance refers to covariance between indicators that can be attributed to methodological designs, and it is typically believed to inflate observed relations (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003). Constructs that have little to no relation may appear to be strongly related in the presence of common method variance. Many authors have provided suggestions and guidelines to reduce the influence of common method variance, such as utilizing longitudinal research designs (Ployhart & Ward, 2011). Unfortunately, these precautions are not always taken, and, even when they are, the effect of common method variance can still be pervasive. For this reason, authors have recommended that researchers should also perform assessments of the influence of common method variance in their results, and Harman's one-factor test is among the most commonly applied (Chang et al., 2010;

Fuller et al., 2016).

To perform Harman's one-factor test, all indicators are assessed via EFA. Several cutoffs exist to determine whether common method variance is concerning when using Harman's one-factor test, but the emergence of one-factor alone as well as the first factor explaining 50 % or more of the variance in indicators are frequently recommended. If the EFA does not produce either of these two features, then common method variance is considered to not be concerning.

Despite the widespread popularity of Harman's one-factor test, several researchers have strongly criticized its use (Gorrell et al., 2011; Min et al., 2016; Rodríguez-Ardura & Meseguer-Artola, 2020), and recent simulation studies cast great doubt upon its validity (Aguirre-Urreta & Hu, 2019; Fuller et al., 2016). Fuller et al. (2016) showed that Harman's one-factor test routinely produces both false positives and false negatives, leaving it unclear whether common method variance is or is not concerning whenever the test is applied. Given the uncertain utility of Harman's one-factor test, it is important to assess its frequency of application, applied cutoffs, and statistical results. Researchers may frequently perform Harman's one-factor test but rarely – if ever – obtain results that indicate the presence of common method variance. If the case, then Harman's one-factor test would be too lenient of an assessment, and researchers should investigate the efficacy of differing cutoffs and/or other approaches to assess common method variance. We propose the two research questions below to investigate this notion. We also assess some of the research questions above regarding Harman's one-factor test (e.g., sample size), but researchers are not expected to report as much information regarding the test as typical EFA. Thus, we do not assess all research questions above regarding Harman's one-factor test.

Research Question 8: What cutoffs are commonly applied for Harman's one-factor test in tourism and hospitality research?
Research Question 9: How much variance is explained by the first factor in Harman's one-factor test in tourism and hospitality research?

2.3. Publication year

We lastly investigate the relation of publication year with all EFA attributes. Standards for EFA change over time. While certain methods may have previously been appropriate, they may be no longer accepted today. For this reason, it is necessary to determine whether those in the field of tourism and hospitality are adapting with these changing standards. It is possible that problematic methods are no longer being applied, but it is also possible that researchers are slow to adapt – resulting in misleading EFA interpretations. Also, investigating publication year can assess whether researchers are becoming more likely to report all aspects of their EFA. With the increased attention to replicability (Maxwell et al., 2015; Shrout & Rodgers, 2018) and access to online repositories for supplemental materials, it would be expected that researchers are more likely than ever to fully report all aspects of their EFAs. We test this notion.

Research Question 10: Does year have a relation with the EFA methods applied in tourism and hospitality research?

3. Method

3.1. Article retrieval and coding

We identified premier journals in tourism and hospitality to review their use of EFA. To do so, we first used the Academic Journals Guide (AJG) (CABS, 2018), which ranks business-relevant journals into five tiers (4*, 4, 3, 2, and 1). The AJG category most relevant to tourism and hospitality is Sector Studies, and we recorded all journals ranked 4 or 3 from this category (none are ranked as 4*). The Sector Studies category, however, also includes journals that are largely irrelevant to tourism and hospitality. For this reason, we cross-referenced each recorded journal with the SCimago Journal & Country Rank categories, and we retained all journals categorized within the Tourism, Leisure, and Hospitality Management category to ensure that the journals are sonly focused on tourism and hospitality. This resulted in a list of six journals: *Annals of Tourism Research*, *International Journal of Contemporary Hospitality Management*, *International Journal of Hospitality Management*, *Journal of Sustainable Tourism*, *Journal of Travel Research*, and *Tourism Management*. Each of these journals was also ranked A* or A on the Australian Business Deans Council (ABDC) Journal Quality List, indicating that they are premier journals in tourism and hospitality. It should be highlighted that identifying a set of journals in this manner is relatively atypical for literature reviews. It was our intent, however, to perform a review of EFA in the premier tourism and hospitality outlets, which identifying outlets in this manner enabled us to achieve.

We then performed searches of these six journals in June 2022 via Google Scholar using the search terms, "Exploratory Factor Analysis" and "Principal Components Analysis". This resulted in an initial list of 1,473 articles. For the following two phases, two coders coded various attributes of these articles. To do so, the coders jointly developed coding guidelines and coded sets of 20 articles until sufficient interrater agreement was achieved (Cohen's κ =.80[2]). Afterwards, they independently coded the articles and conferred on difficult coding decisions.

The coders first reviewed each article for the use of EFA, which reduced the list to 1,286 articles. Most of the articles removed in this phase mentioned EFA in providing justifications for their use of CFA or partial least-squares structural equation modeling, but EFA was not applied in the article. We also chose not to include articles that performed EFA for the sole purpose of creating indicator parcels for structural equation modeling, as expectations in reporting greatly differ when applying EFA for this purpose compared to typical applications. The coders then coded each article and reported EFA on the attributes below. Our literature review database after coding all articles is provided in Supplemental Material A.

Purpose. The purpose of each EFA was recorded as either investigating factor structures, Harman's one-factor test, or both.

Publication Date. The publication date of each article was recorded.

Sample Size. The sample size was recorded. If the authors did not specifically state their sample size for the EFA, the coders recorded the sample size of the respective study (assuming no missing data).

Number of Indicators. The number of initial indicators was recorded. The number of indicators was not recorded (i.e., "Unknown") if the authors reported removing indicators via their EFA process but only disclosed the final number of retained indicators.

Data Quality Checks. The coders recorded whether Bartlett's test and KMO test were conducted.

Factor Extraction. The factor extraction method was recorded as either PCA, PAF, Other, or Unknown.

Factor Retention. The factor retention method was recorded as Kaiser's criterion, Scree Plot, Parallel Analysis, Other, or Unknown. An EFA could have multiple categories recorded.

Number of Retained Factors. The coders recorded the number of retained factors.

Variance Explained. The coders recorded the final amount of variance explained in the indicators by both the first retained factor as well as all the retained factors.

Factor Rotation. The factor rotation method was recorded as either Orthogonal or Oblique. It was also recorded as either Varimax, Oblimin, Promax, or Other.

Factor Loading Cutoffs. The primary loading cutoff, cross-loading cutoff, and difference between the primary and cross-loading cutoff

[2] Due to the manner that certain aspects were coded, a raw inter-rater agreement cutoff of 80% was used for these aspects.

were recorded.

Factor Loadings. The smallest primary loading, largest cross-loading, and smallest difference between a primary and cross-loading were recorded.

One-Factor Cutoff. The cutoff used for the one-factor test was recorded as either one emergent factor, 50 % of the variance explained by the first factor, or other.

Domain of Study. Each article was coded into one of six content area categories: Marketing (1,259 EFAs), Management and Human Resources (Management/HR) (657 EFAs), Psychology (191 EFAs), Management Information Systems and Human-Computer Interaction (MIS/HCI) (112 EFAs), Economics (36 EFAs), and Supply Chain (16 EFAs). In general, marketing studies investigated the dynamics of customers; management/HR studies investigated the dynamics of employees and organizations; psychology studies investigated the dynamics of those not directly involved with the organization or product (e.g., residents); MIS/HCI studies investigate the dynamics of technology; economics studies investigate macro dynamics at higher levels than organizations (e.g., regions); and supply chain investigates the dynamics of business-to-business interactions. While some articles could represent the overlap of multiple areas, we coded each article solely into the content area that it most represented.

4. Results

We first assessed the articles for outliers in the number of reported EFAs. On average, the included articles reported 1.77 EFAs (Std. Dev. = 1.63). Seventeen articles had z-scores larger than four regarding their number of reported EFAs: Six articles reported nine EFAs (z-score = 4.44), six articles reported 10 EFAs (z-score = 5.05), one article reported 11 EFAs (z-score = 5.66), two articles reported 12 EFAs (z-score = 6.28), and two articles reported 13 EFAs (z-score = 6.89). While these articles had large z-scores, it was difficult to determine when an article was a clear outlier. We did not remove any articles from analyses, but we do report sensitivity analyses to address concerns of a single article having an undue influence. The primary text reports our results when weighting each EFA equally, which causes most articles to be represented multiple times in our dataset. Supplemental Material B reports our results when averaging the EFA coding decisions together within each article, such that each article is represented only once in our dataset but each EFA is weighted differently. By providing both sets of analyses, we address concerns regarding the weighting of articles and EFAs.

Further, we also conducted another set of sensitivity analyses. When coding EFAs, we interpreted the analytical decisions exactly as stated by the authors. For example, if an author noted that they used PCA for their first EFA but did not specify for their second, we coded the first EFA as using PCA and the second as "Unknown". Some readers may believe that it is appropriate to assume that PCA was used for both EFAs. For this reason, we created another dataset wherein we assumed that all EFAs performed in the same article utilized the same analytic decisions. In the example just provided, for instance, we would have coded both EFAs as using PCA. We then recalculated our results using this alternative dataset, and the findings are provided in Supplemental Material C. None of our inferences differed between our primary analyses and both of these sensitivity analyses, supporting the robustness of our results.

Lastly, we replicated all findings provided below with the results separated by the studies' content area, which can be found in Supplemental Material D. Our results largely replicated when reconducted for each content area separately, which further supports the robustness of our findings. Readers interested in a specific domain of tourism and hospitality research can refer to these analyses to understand practices in their specific domain of study.

4.1. Factor structure investigations

Tables 1, 2, and 3 provide the coding results of EFAs performed for

Table 1
Percentile Results Regarding EFA for Factor Structure Investigations.

	Sample Size	# of Indicators	Sample Size to Indicator Ratio	Primary Loading Cutoff	Secondary Loading Cutoff	Difference Cutoff	Smallest Primary Loading	Largest Secondary Loading	Smallest Difference	Total Variance Explained
n	2,027	1,974	1,952	677	124	23	1,452	181	160	1,409
10th Percentile	119	4	5.96	0.40	0.30	0.12	0.42	0.25	0.01	53.27
20th Percentile	178	5	8.90	0.40	0.31	0.20	0.47	0.32	0.03	58.12
30th Percentile	215	8	12.40	0.40	0.40	0.20	0.51	0.35	0.07	61.20
40th Percentile	270	11	16.50	0.40	0.40	0.20	0.54	0.39	0.11	63.83
50th Percentile	318	14	22.16	0.40	0.40	0.20	0.57	0.42	0.15	66.70
60th Percentile	380	18	31.09	0.50	0.40	0.20	0.62	0.45	0.20	68.82
70th Percentile	438	23	45.27	0.50	0.40	0.20	0.68	0.48	0.27	71.88
80th Percentile	535	28	70.50	0.50	0.40	0.20	0.73	0.50	0.38	75.15
90th Percentile	773	37	113.69	0.50	0.50	0.20	0.81	0.53	0.50	80.17

Note: n represents the number of EFAs used to calculate the provided percentile values. For instance, we coded the sample size of 2,027 EFAs; however, we coded the primary loading cutoff of only 677 EFAs, as authors much less frequently provided their primary loading cutoff than their sample size.

Table 2
Median Sample Sizes Differentiated by Number of Indicators and Factors.

	1 Factors	2 Factors	3 Factors	4 Factors	5 Factors	6 Factors	7 Factors	8 Factors	9+ Factors
5 Indicators	336 (430)	245 (65)	408 (6)	–	–	–	–	–	–
10 Indicators	357 (76)	381 (92)	332 (71)	270 (30)	368 (7)	–	–	–	–
15 Indicators	298 (25)	283 (45)	375 (84)	284 (71)	304 (26)	–	–	–	–
20 Indicators	324 (5)	400 (17)	336 (46)	302 (62)	368 (41)	255 (12)	404 (9)	–	–
25 Indicators	–	433 (10)	370 (29)	225 (39)	367 (32)	307 (39)	371 (15)	435 (5)	–
30 Indicators	–	–	427 (14)	264 (24)	332 (27)	414 (26)	353 (15)	325 (12)	330 (6)
35 Indicators	–	–	–	365 (15)	280 (17)	380 (17)	307 (8)	313 (5)	–
40 Indicators	–	–	–	366 (7)	225 (11)	278 (12)	399 (11)	409 (7)	331 (10)
45+ Indicators	–	–	–	381 (6)	247 (10)	331 (20)	355 (15)	291 (10)	343 (36)

Note: Rows indicate how many initial indicators were included in EFAs, and columns indicate how many emergent factors were produced from EFAs. The number of indicators were rounded to the nearest fifth to create an appropriate number of categories. The first number of each cell represents the median sample size of that condition, whereas the number in parentheses represents the number of EFAs included in that condition. Only factor and indicator combinations with five or more representative studies are included.

Table 3
Frequency of Analytic Decisions Regarding EFA for Factor Structure Investigations.

	Frequency
Data Inspection	
Bartlett's	856 (42 %)
KMO	1,004 (49 %)
Factor Extraction	
PCA	1,071 (52 %)
PAF	177 (9 %)
Other	77 (4 %)
Unknown	725 (35 %)
Factor Retention	
Kaiser	781 (38 %)
Scree	193 (9 %)
Parallel	45 (2 %)
Other	17 (1 %)
Unknown	1,192 (58 %)
Rotation Method	
Varimax	710 (57 %)
Other Orthogonal	22 (2 %)
Oblimin	57 (5 %)
Promax	109 (9 %)
Other Oblique	57 (5 %)
Unknown	292 (23 %)

Note: The factor extraction and rotation method categories are mutually exclusive, whereas the data inspection and factor retention categories are not mutually exclusive. For rotation method, only EFAs reporting the retention of multiple factors were included.

factor structure investigations in tourism and hospitality research. Researchers of tourism and hospitality utilize larger sample sizes for EFA than discovered in reviews of other domains (Conway & Huffcutt, 2003; Howard, 2016; Watkins, 2018). The median sample size was 318 participants, and the median participant-to-indicator ratio was 22. Both veer towards larger absolute and participant-to-indicator recommendations (Hinkin, 1995, 1998; Reio & Shuck, 2015). We also assessed whether researchers base their samples on their number of indicators and expected number of factors by conducting a linear regression analysis wherein sample size was the dependent variable and the number of indicators and factors were independent variables. For this specific analysis, we also rescaled the largest 1 % of sample sizes (>2560), indicators (>79), and factors (>11) to the numbers listed in parentheses to prevent outliers from having an undue influence. In this analysis, the number of indicators did not have a statistically significant effect ($\beta = 0.06$, $t = 1.54$, $p = .12$), but the effect of the number of emergent factors was statistically significant ($\beta = -0.10$, $t = -2.49$, $p = .01$). Table 2 presents median sample sizes separated by the number of indicators and emergent factors such that readers can observe the relative consistency in sample sizes. While tourism and hospitality researchers utilize relatively large sample sizes for their EFAs, they appear to not be based on attributes that determine the necessity of larger sample sizes. In fact, sample sizes tended to decrease as the number of expected factors increased, contrary to common recommendations for sample size when conducting EFA.

Forty-two percent of EFAs reported a Bartlett's test, and forty-nine percent of EFAs reported the KMO test. Again, this figure is much larger than prior reviews of EFA for other fields of study (Conway & Huffcutt, 2003; Howard, 2016; Watkins, 2018), and it appears that tourism and hospitality researchers often but do not universally report screening their data.

The second step of EFA is determining the factor extraction approach. Tourism and hospitality researchers are strongly reliant on the principal components approach, as PCA was used for 52 % of all EFAs for factor structure investigations. PAF was used for only 9 %, and other factor extraction approaches were used for 4 % (e.g., maximum likelihood). Thirty-five percent of EFAs for factor structure investigations did not report their factor extraction approach.

The third step is determining the number of factors to retain. It was most common for researchers to not directly state their approach for doing so, which represented 58 % of EFAs for factor structure investigations. The most common criteria were the Kaiser criterion (38 %), followed by the visual scree plot analysis (9 %), parallel analysis (2 %), and other techniques (1 %). Seven percent of EFAs for factor structure evaluations utilized both the Kaiser criterion and the visual scree plot analysis, whereas only 1 % used a different combination of approaches. Thus, tourism and hospitality researchers appear to apply sub-optimal methods for determining the number of factors to retain from their EFAs for factor structure investigations.

The fourth step is determining the factor rotation method, for which we only coded articles that reported the retention of more than one factor. Tourism and hospitality researchers are reliant on orthogonal rotation methods, as varimax was undoubtedly the most popular factor rotation method (57 %). Other orthogonal methods were used 2 % of the time. Alternatively, oblique methods were much less frequently used,

Table 4
Percentile Results Regarding EFA for Harman's One-Factor Tests.

	Sample Size	# of Indicators	Sample Size to Indicator Ratio	# of Factors	Variance Explained by First Factor
n	241	234	234	117	192
10th Percentile	198	19	5.50	4	18.13
20th Percentile	230	22	7.29	4	23.07
30th Percentile	281	25	9.20	5	26.03
40th Percentile	318	28	10.57	6	29.17
50th Percentile	365	30	12.27	6	31.13
60th Percentile	412	32	14.26	7	33.18
70th Percentile	464	36	16.50	7	36.27
80th Percentile	557	40	19.80	8	39.31
90th Percentile	721	47	26.11	11	43.00

Note: n represents the number of EFAs used to calculate the provided percentile values. For instance, we coded the sample size of 241 EFAs; however, we coded the variance explained by the first factor of only 192 EFAs, as authors much less frequently provided their variance explained by the first factor than their sample size.

with oblimin being used 5 %, promax being used 9 %, and other oblique methods being used 4 % of the time. Twenty-three percent of EFAs for factor structure investigations did not have an associated rotation method reported.

The fifth step is factor loading interpretations. Some articles reported an a priori primary loading cutoff (33 %), whereas very few reported an a priori secondary loading cutoff (8 %) or difference cutoff (2 %). Of articles that reported a priori loading cutoffs, the most common primary loading cutoff was 0.40 (46 %), which was also true of the most common secondary loading cutoff (56 %). The most common difference cutoff was 0.20 (83 %). Factor loadings were generally much stronger than these cutoffs, however. The median smallest primary loading was 0.57, whereas the median largest secondary loading was 0.42. The median smallest difference between primary and secondary loadings was 0.15. These results indicate that researchers follow criteria for primary loadings, but they are much less stringent regarding secondary loadings. While not a part of our review, we also recorded the amount of variance explained by all retained factors. The median amount of variance explained was 67 %, indicating that tourism and hospitality researchers explain the majority of variance in their indicators when performing EFA.

4.2. Harman's One-Factor test

We focus on four aspects of reporting Harman's one-factor test: sample size, cutoffs, number of factors emerged, and variance explained by the first factor (Table 4). The median sample size was 365, and the median participant-to-indicator ratio was 12. While the former was larger than EFAs for factor structure investigations, the latter was smaller.

Three cutoffs were most commonly used for one-factor tests in prior articles: 50 % or more of the variance explained by the first factor (43 %), one emergent factor (5 %), and a combination of these two (14 %). Four percent of one-factor tests used an alternative criterion, and 35 % did not clearly state their criterion. The median number of emergent factors from the one-factor tests was six, and the median variance explained by the first factor was 31 %. Only two one-factor tests produced a one-factor solution, but both articles used the 50 % criteria. Only one one-factor test produced a first factor that explained more than 50 % of the variance in indicators, but the researchers nevertheless claimed that this result indicated "no relevant method bias". Therefore, no researcher failed Harman's one-factor test.

4.3. Publication year

We lastly applied a series of analyses to determine whether the analytical decisions above were significantly related to the publication year. Due to space concerns, we do not fully report these findings in the primary text, but we instead provide them in Supplemental Material E and summarize them in Table 5. We presently recap these results via the

Table 5
Regression and Binominal Regression Results of Year Predicting EFA Attributes.

EFA for Factor Structure Investigations			
	Year		Year
1.) Sample Size	β = 0.03	2.) Participant-to-Indicator Ratio	β = 0.03
3.) Bartlett's Test	Z = 9.72***	4.) KMO Test	Z = 9.93***
5.) Unknown Factor Extraction	Z = 3.88***	6.) PCA	Z = −7.49***
7.) PAF	Z = 4.61***	8.) Other Factor Extraction	Z = 3.43**
9.) Unknown Factor Retention Method	Z = 3.39**	10.) Kaiser Criterion	Z = −2.31**
11.) Visual Scree Plot Analysis	Z = −6.29***	12.) Parallel Analysis	Z = 3.75***
13.) Other Factor Retention Method	Z = 0.81	14.) Unknown Factor Rotation Method	Z = 2.28*
15.) Varimax	Z = −4.74***	16.) Orthogonal	Z = −5.15***
17.) Oblimin	Z = 2.19**	18.) Promax	Z = 5.68***
19.) Oblique	Z = 4.29***	20.) Primary Loading Cutoff Provided	Z = −2.42*
21.) Primary Loading Cutoff	β = 0.20***	22.) Primary Loading	β = 0.24***
23.) Cross-Loading Cutoff Provided	Z = 1.52	24.) Cross-Loading Cutoff	β = −0.07
25.) Cross-Loading	β = −0.14	26.) Loading Difference Cutoff Stated	Z = −0.74
27.) Factor Loading Difference Cutoff	β = 0.10	28.) Factor Loading Difference	β = 0.24***
EFAs for Harman's One-Factor Tests			
	Year		Year
29.) Sample Size	β = −0.02	30.) Participant-to-Indicator Ratio	β = 0.02
31.) Variance Explained by First Factor	β = −0.01		

Note: β values represent results of regression analyses with year as the sole predictor. Z values represent results of binominal regression analyses with year as the sole predictor.

EFA steps presented above.

First, sample sizes and participant-to-indicator ratios did not have a significant relation with year, whether considering EFA for factor structure investigations or Harman's one-factor test (all $p > .05$). Researchers are increasingly applying Bartlett's test and the KMO test (both $p < .001$), which had the two strongest relations with publication year. Second, PCA had a negative relation with year ($p < .001$), whereas researchers are increasingly applying PAF ($p < .001$), other factor extraction approaches ($p < .01$), as well as not reporting their approaches altogether ($p < .001$). Third, researchers are applying both the Kaiser criterion ($p < .01$) and visual scree plot analyses ($p < .001$) less often, whereas they are increasingly applying parallel analyses ($p < .001$) or not reporting their factor retention approaches ($p < .01$). Fourth, the use of varimax and orthogonal rotations are becoming less common ($p < .001$), and the use of oblimin ($p < .01$), promax ($p < .001$), and oblique rotations ($p < .001$) are becoming more common. The failure to report factor rotations likewise had a positive relation with publication year ($p < .05$). Fifth, higher primary loading cutoffs are being used over time ($p < .001$), which result in higher primary loadings ($p < .001$). On the other hand, publication year had a negative relation with providing a primary loading cutoff altogether ($p < .05$), and it did not have a significant relation with cross-loading cutoffs, factor loading difference cutoffs, or the size of cross loadings ($p > .05$). Publication year did, however, have a significant relation with the difference between primary and secondary loadings ($p < .001$). Lastly, publication year did not have a significant relation with the variance explained by the first factor in Harman's one-factor test ($p > .05$).

Researchers appear to be gradually applying recommended methods more often, but it should be highlighted that these trends do not indicate that recommended methods are now more commonly applied than prior standards. For instance, our estimated marginal means indicated that orthogonal rotations were applied approximately 80 % in 1990 to 50 % in 2021, whereas oblique rotations were applied approximately 5 % in 1990 to 25 % in 2021 (unknown increased from approximately 15 % in 1990 to 25 % in 2021). We direct readers to Supplemental Material E for visual representations in the changes of estimated marginal means over time.

5. Discussion

The goal of the current article was to provide a review of EFA practices in tourism and hospitality research, which were separated by EFAs for factor structure investigations and EFAs for Harman's one-factor test. EFAs for factor structure investigations can be detailed by their five steps (Reio & Shuck, 2015; Watkins, 2018). First, researchers typically collected sufficient sample sizes, but these sizes were not based on the number of indicators or emergent factors – two primary aspects that necessitate larger sample sizes. Bartlett's test and the KMO test were used in conjunction with about half of EFAs, which was much more than reviews of other fields (Conway & Huffcutt, 2003; Howard, 2016; Watkins, 2018). Second, PCA was vastly more popular than PAF, and tourism and hospitality researchers are strongly reliant on the principal component model. Third, the Kaiser criterion alone was the most popular approach to determine the number of factors to retain, and few articles utilized other approaches for factor retention decisions. Fourth, despite prior concerns, orthogonal rotations were also vastly more popular than oblique rotations, with varimax being the most popular factor rotation method. Fifth, authors were consistent in their use of cutoffs. The most common primary loading cutoff and secondary loading cutoff was 0.40, whereas the most common cutoff for the difference between the two was 0.20. Researchers regularly exceeded these cutoffs – for both better and worse. Many primary loadings were larger than 0.40, but many secondary loadings were larger than 0.40. Lastly, a large amount of EFA steps were not reported in the primary studies, leaving it unknown whether the reported EFAs were conducted correctly.

Regarding Harman's one-factor tests, researchers used sufficient sample sizes based on absolute recommendations, but their sample sizes adhered to smaller guidelines when based on participant-to-indicator ratios. More importantly, the most common cutoff criterion for one-factor tests was the first factor explaining 50 % or more of the variance in the indicators, and only one article reported failing this criterion; however, the authors of this one article still claimed that their results did not indicate the presence of method bias, and, in fact, no authors found one-factor tests to indicate problematic common method bias. Therefore, it appears that Harman's one-factor test is a poor indicator of common method bias as no researcher ever fails the test.

Our analyses involving publication year showed that researchers are gradually applying recommended approaches more frequently, but most recommended approaches (e.g., oblique rotations) have yet to become the dominant approach in tourism and hospitality research. These analyses also showed that researchers have become less likely to report their approaches for EFA, including retention and rotation methods. This result is surprising, given recent attention to replicability and open science practices (Maxwell et al., 2015; Shrout & Rodgers, 2018).

The use of EFA can be significantly improved in light of these results, and we pose several implications and directions for future research below. Because our results largely replicated when reconducted separately for each research domain (and therefore similar concerns can be seen for all research domains), scholars of all areas of tourism and hospitality research should take note of our recommendations. Our findings are also summarized in Table 6, along with brief summaries of recommended practices discussed below.

5.1. Implications and future directions

5.1.1. Factor structure investigations

Below, we provide many recommendations for the use of EFA for factor structure investigations. These recommendations reflect prior suggestions and simulation study results in the broader study of business and the social sciences, and they generally align with recent trends in conducting EFA within tourism and hospitality research. This provides assurances that these recommendations align with best practices both within and outside of tourism and hospitality research, but also that tourism and hospitality researchers are gradually adopting improved approaches. To provide more clarity regarding these recommendations, we provide a summary and checklist in Table 7 for future researchers to follow when conducting their analyses.

We would first like to highlight, however, that these recommendations should be considered in the broader context of measurement. EFA provides evidence for the psychometric properties of measures. This evidence should be replicated via CFA using an alternative sample to ensure that the initial results were not spurious effects, and researchers should also seek validity evidence to provide support that their observed factors gauge intended constructs. While EFA and CFA can support that indicators assess a common factor, validity evidence is required to support that these factors are accurate representations.

Three types of validity are particularly valuable in research – convergent, concurrent, and discriminant (Clark & Watson, 1995; Hinkin, 1995, 1998). Convergent validity, the extent that two measures of the same construct relate, can provide significant support that a measure assesses its intended construct, but this evidence is not possible to obtain when multiple prior measures do not exist. Concurrent validity is the extent that a measure relates to measures of conceptually associated constructs, such as a self-esteem measure strongly relating to a self-efficacy measure. Discriminant validity is the extent that a measure does not relate to measures of different constructs, which can be supported by both showing that a measure is not redundant with another measure of a different construct as well as supporting that a measure is largely unrelated to a measure of an irrelevant construct (Clark & Watson, 1995; Hinkin, 1995, 1998). Showing that a self-esteem measure is not excessively related to a self-efficacy measure could satisfy the former, whereas showing that a self-esteem measure is largely unrelated

Table 6
Article Summary Table.

Research Questions	Current Practices	Recommended Practices
What sample sizes are used for EFA in tourism and hospitality research?	Average of 322 participants and average participant-to-indicator ratio of 22.	Adhere to recent recommendations, such as >300 participants, >10 participants per indicator, and estimates based on the number of indicators and expected factors.
How frequently are Bartlett's test and the KMO test applied in tourism and hospitality research?	Bartlett's test was performed in 42 % and KMO test was performed in 49 % of EFAs.	Bartlett's test and KMO test should always be conducted.
How frequently are PCA and PAF applied in tourism and hospitality research?	PCA was used in 52 %, PAF was used in 9 %, and no method was reported in 35 % of EFAs.	Factor extraction method should be based on researcher's rationale, whether PCA or PAF.
How frequently are various factor retention methods applied in tourism and hospitality research?	No method was reported in 58 %, Kaiser criterion was used in 38 %, visual scree plot analysis was used in 9 %, and other methods were used in 1 % of EFAs. Only 8 % used multiple approaches.	Researchers should no longer use the Kaiser criterion, and they should instead use multiple other approaches together, such as scree plot analysis and parallel analysis.
How frequently are various factor rotation methods applied in tourism and hospitality research?	Varimax was applied in 57 %, oblimin was applied in 5 %, promax was applied in 9 %, and no method was reported in 23 % of EFAs.	Researchers should apply oblique rotations, such as oblimin or promax.
What cutoffs are commonly applied for primary loadings, cross-loadings, and the difference between primary and cross-loadings in tourism and hospitality research?	Most common primary loading cutoff was 0.40, most common secondary loading cutoff was 0.40, and most common difference cutoff was 0.20. Most articles did not report their cutoffs.	Unless justifications can be provided for other cutoffs, use primary loading cutoff of 0.40, secondary loading cutoff of 0.30, and difference cutoff of 0.20. Report observed factor loadings relative to their percentile values in Table 1. Interpret loadings in a holistic manner.
What are the smallest primary loadings, largest cross-loadings, and smallest difference between primary and cross-loadings reported in tourism and hospitality research?	Median smallest primary loading was 0.57, median largest secondary loading was 0.42, and median smallest difference between primary and secondary loadings was 0.15.	
What cutoffs are commonly applied for Harman's one-factor test in tourism and hospitality research?	Most common cutoffs were: 50 % or more of the variance explained by the first factor (43 %), one emergent factor (5 %), and a combination of these two (14 %). Cutoff not provided in 35 % of EFAs.	Refrain from using Harman's one-factor test until future research can better support its accuracy in assessing common method variance, perhaps using different cutoffs or analytic approaches.
How much variance is explained by the first factor in Harman's one-factor test in tourism and hospitality research?	Median variance explained by the first factor was 31 %. No application of Harman's one-factor test found common method variance to be concerning.	
Does year have a relation with methods applied in EFAs for factor structure investigations and Harman's one-factor test in tourism and hospitality research?	Researchers are gradually applying recommended approaches more frequently, but most recommended approaches have yet to become dominant. Researchers are also becoming less likely to report their EFA approach.	Ensure that all analytic decisions and results of EFA are fully reported, even if reported solely in supplemental materials. Ensure that justifications are provided for each decision, such as the use of PCA or PAF.

to a color preference scale could satisfy the latter (Miller & Simmering, 2022).

While EFA is an important statistical tool to ensure the psychometric properties of measures, researchers should examine validity evidence associated with their scales – even when EFA results are favorable. If validity evidence is not examined, researchers' indicators may assess a common factor, but this factor may not represent their intended construct. With this noted, we provide recommendations for the use of EFA for factor structure investigations.

5.1.2. Step 1: Data Assessment

Tourism and hospitality researchers should continue utilizing large sample sizes for EFA (e.g., >300 participants and >10 participant-to-indicator ratio), but they should also be cognizant that even larger samples are necessary when using an extreme number of indicators or expecting an extreme number of emergent latent factors (Gaskin & Happell, 2014; Rouquette & Falissard, 2011). Present guidelines, however, do not provide firm recommendations regarding appropriate sample sizes when considering both of these criteria. We call on quantitative-oriented researchers to address this concern. Specifically, simulation studies are needed to determine the statistical power associated with specific sample sizes given certain numbers of indicators and expected factors that are common in tourism and hospitality research. Rouquette and Falissard (2011) provided initial simulation results regarding this research question, but they did not provide estimates for the number of indicators and expected factors often seen in tourism and hospitality research. Instead, their simulations were focused on parameters typically seen in psychiatric research. Once simulations are performed that are catered to parameters seen in tourism and hospitality studies, future researchers could have more assurances in the validity of their EFA results – assurances that cannot presently be provided.

On the other hand, it is reassuring to see that researchers of tourism and hospitality are more commonly applying Bartlett's test and the KMO test than other fields of study, but these assumption checks are by no means universal when conducting EFA. Suggestions to perform these analyses may not fully resonate until simulation studies demonstrate the influence of violated assumptions on EFA results. Prior authors (e.g., Rouquette & Falissard, 2011) have noted that violated assumptions impact sample size requirements, such that larger sample sizes are needed in the presence of these influences, but the full extent of their impact is unknown. Prior sample size recommendations based on absolute values and participant-to-indicator ratios may be particularly inaccurate under realistic conditions. We again call on quantitative-oriented researchers to conduct simulation studies on these present uncertainties.

5.1.3. Step 2: Factor Extraction

Our results demonstrated that the principal component model (e.g., PCA) is clearly preferred by tourism and hospitality researchers, and the common factor approach (e.g., PAF) is only slightly growing in popularity; however, we saw few justifications for the application of the principal component approach rather than the common factor approach. Rich conceptual discussions can be seen in other fields, such as management and psychology, for their clear preference for the common factor approach (Hinkin, 1995, 1998; Jain & Shandliya, 2013; Preacher & MacCallum, 2003). It is possible that tourism and hospitality

Table 7
Recommended Practices for Conducting EFA for Factor Structure Investigations.

Step	Recommendations	Check
Pre-Analysis	Review current literature to identify recent changes to recommended EFA best practices, which may be discovered via recent review articles or simulation studies. Apply these new best practices in favor of older recommendations, including those provided below.	☐
Step 1. Data Quality Checks	Obtain a sample size that adheres to recent recommendations for EFA, such as more than 300 participants, a participant to indicator ratio of 10 to 1, and estimates based on the number of indicators and expected number of emergent factors.	☐
	Conduct typical assessments and corrections for data quality, including issues of missing data, outliers, and insufficiently motivated responders.	☐
	Perform Bartlett's test and the KMO test.	☐
Step 2. Factor Extraction	Determine whether a principal components or common factor approach is better suited for the research question at hand, which will likely be determined by the need to model total variance or shared variance alone. Provide rationale for this decision in manuscript.	☐
	If a principal components approach is called for (e.g., total variance), perform principal components analysis (PCA).	☐
	If a common factor approach is called for (e.g., shared variance), perform principal axis factoring (PAF).	☐
	Due to its assumptions regarding normality, maximum likelihood (ML) should not be the default approach when a common factor approach is required (e.g., shared variance); however, ML should be applied if fit indices are required for the research question at hand.	☐
Step 3 – Factor Retention	Do not apply the Kaiser criterion alone.	☐
	Apply both visual scree plot analysis and parallel analysis.	☐
	Utilize any other preferred factor retention approaches.	☐
	Perform holistic factor retention decisions, wherein the relative merits of multiple factor retention approaches are considered.	☐
Step 4 – Factor Rotation	Apply oblique rotations, as they can account for correlations among factors. Two recommended oblique rotations are oblimin and promax.	☐
	If an orthogonal rotation is absolutely required, apply varimax.	☐
Step 5 – Indicator Assessment	Unless other cutoffs can be sufficiently justified, use a primary loading cutoff of 0.40, secondary loading cutoff of 0.30, and difference cutoff of 0.20.	☐
	Reference Table 1 to identify relative percentiles for strength of primary loadings, secondary loadings, and their difference. Report observed factor loadings relative to their percentile values.	☐
	Interpret factor loadings in a holistic manner, such that primary and all cross-loadings are considered.	☐
Post-Analysis	Fully report all analytical decisions and the rationale behind the decisions. Likewise, report all statistical results. Supplemental materials may be required to fully report this information.	☐

researchers regularly apply PCA due to norms and traditions rather than theoretical alignment with their intents for conducting EFA. When conducting EFA, future researchers should clearly delineate why they apply PCA, PAF, or a different factor extraction method. These arguments should be based on whether the researcher's purpose is primarily for data reduction, explaining the total variance of indicators, explaining the shared variance of indicators, or another reason. By mandating that authors adequately justify their analytical decisions, the field of tourism and hospitality research can ensure that the appropriate methods are applied with their associated intents – whether the prevalent method remains PCA or becomes a different approach (e.g., PAF).

5.1.4. Step 3: Factor Retention

The most popular approach to determine the number of factors to retain was the Kaiser criterion, which was even evident in the estimated marginal means for the year 2021. As mentioned, the Kaiser criterion is among the least accurate approaches to determine the number of factors to retain, and a multitude of authors have called for it to be no longer applied (Braeken & Van Assen, 2017; Courtney & Gordon, 2013; Patil et al., 2008). We believe that this is the largest weakness of authors applying EFA in tourism and hospitality research. Moving forward, reviewers and editors should no longer allow researchers to solely apply the Kaiser criterion. They should instead expect researchers to apply a combination of methods, as each method has its strengths and weaknesses. We particularly recommended that researchers should apply both visual scree plot analyses as well as parallel analyses. While the former does include subjective elements, it enables researchers to assess in greater depth which resulting factor structure best aligns to their theoretical perspective – a pivotal aspect in determining the number of factors to retain. The latter is among the most accurate approaches for determining the number of factors to retain, and it does require some researcher interpretation of results. Particularly, Lim & Jahng (2019) recently supported that parallel analysis results can be valid when selecting the factor that meets the cutoff as well as the factors before and after. For this reason, these authors recommended that researchers should investigate the validity of all three factor solutions and choose the one that produces results that best adhere to theory. Therefore, applying these well-established approaches instead of the Kaiser criterion alone can produce EFA results that are significantly more accurate than those commonly seen in the literature.

5.1.5. Step 4: Factor Rotation

Tourism and hospitality researchers clearly prefer orthogonal rotations instead of oblique, but justification for utilizing this family of rotations was very rarely provided. The choice of orthogonal rotations has few adequate justifications. Some authors claim that small intercorrelations between factors indicate that ignoring this variance is appropriate (Corner, 2009), but oblique rotations can accurately model covariance between factors – no matter how small or large (Harman, 1976; Howard, 2016; Osborne, 2015). We urge tourism and hospitality researchers to apply oblique rotations, such as oblimin and promax, as these can be justified across a broader range of applications. By applying oblique rotations, more accurate factor analytic results can be obtained than the current practice of applying orthogonal rotations.

5.1.6. Step 5: Indicator Assessment

Few concerns can be expressed regarding the treatment of primary loadings in tourism and hospitality research. Adequate primary factor loading cutoffs were applied, and researchers almost always exceeded these cutoffs. Concern can be expressed regarding the treatment of secondary factor loadings, however. Secondary factor loadings represent contamination, such that indicators with large secondary loadings included within final measures represent multiple constructs. If included, then these indicators could inflate observed relations, causing the researcher to make inappropriate theoretical conclusions (Rouquette & Falissard, 2011; Hair et al., 2018). It should be strongly questioned, therefore, whether secondary loading cutoffs should be as strong as primary loading cutoffs. Many other fields of study (e.g., management, psychology) use smaller cutoffs for secondary loadings than primary loadings to ensure that their scales do not include construct contamination. For instance, it is common for researchers to use a 0.50 cutoff for primary loadings but a 0.30 cutoff for secondary loadings (Conway & Huffcutt, 2003; Reio & Shuck, 2015; Watkins, 2018). Similarly, few authors applied a cutoff regarding the difference between primary and secondary loadings, which could also ensure that construct contamination is not present. Of the few authors that did apply a difference cutoff, the most common cutoff was 0.20, which has been recommended in other fields of study (Howard, 2016).

We recommend that tourism and hospitality researchers should be more stringent regarding their treatment of secondary loadings, especially considering the increased attention given to discriminant validity and empirical separation of theoretically distinct constructs in the broader study of business (Henseler et al., 2015; Rönkkö & Cho, 2020). Unless other cutoffs can be theoretically justified, we recommend that researchers should apply the cutoffs recommended by Howard (2016): primary loadings should be greater than 0.40, secondary loadings should be less than 0.30, and the difference between primary and secondary loadings should be greater than 0.20. These reconditions are similar to cutoffs applied in tourism and hospitality research, but the secondary loading cutoff is smaller than current widespread secondary loading cutoffs.

Further, the current article provided percentile values for primary loadings, secondary loadings, and their difference. Future researchers should utilize these percentiles to detail the strength of their observed loadings. For instance, a researcher could note that their primary factor loadings were in the 70th percentile, whereas their secondary loadings were in the 30th percentile based on our results. By doing so, readers could immediately understand that their factor loadings were superb, providing more confidence in the accuracy of their measurement tools. Such an approach would be superior to dichotomous cutoff assessments.

5.2. Harman's One-Factor tests

We provided evidence that Harman's one-factor test has never indicated problematic method bias when applied in our reviewed tourism and hospitality journals. When paired with recent simulation studies (e.g., Fuller et al., 2016), these results cast very strong doubts regarding the validity of Harman's one-factor test. These collective findings can spark two directions for future research. It is possible that Harman's one-factor test is valid but current cutoffs are inappropriate. For instance, some researchers apply a cutoff of 40 % of variance explained by the first factor (Kolar & Čater, 2018; Wang et al., 2020). Future research should perform simulation studies to determine whether alternative cutoffs could cause Harman's one-factor test to produce more accurate findings and better assessments of method bias. Alternatively, it is possible that Harman's one-factor test cannot provide accurate assessments no matter the cutoff. If the case, then researchers should seek alternative statistical approaches. Harman's one-factor test, in theory, serves a useful function. It is beneficial for researchers to have assurances that method bias did not unduly influence their observed results. By finding a suitable replacement, future researchers should assure that their newly-developed statistical approach serves a very useful function – not only for tourism and hospitality researchers but instead researchers from all fields of study. Therefore, these two possible directions for future research appear to be quite pertinent, given the possibility of their widespread implications.

5.3. Publication year

We repeatedly observed that researchers are becoming less likely over time to report aspects of their EFAs, such as their factor extraction or rotation approaches. This finding is both surprising and concerning. Authors in business and the social sciences have strongly stressed the necessity for research to be replicable, leading to much discourse regarding the "replication crisis" (Maxwell et al., 2015; Shrout & Rodgers, 2018). Without fully reporting all aspects of EFAs, it is difficult for subsequent researchers to design replication studies and determine whether new findings indeed replicate original results. We urge future researchers to fully report their EFAs in supplemental materials, as we assume that many researchers do not fully report their EFAs in primary texts due to word and page limits. We also urge future researchers to utilize open science repositories (e.g., OSF.io), which enable researchers to upload their findings to permanent online databases. By using these repositories, editors and reviewers can also have more confidence that researchers' data collection and analyses were performed in an ethical and appropriate manner, providing large benefit beyond the reporting of EFA alone.

5.4. Limitations

As with all studies, certain limitations should be noted. To perform our review of EFA in tourism and hospitality research, we selected six journals. We chose these journals due to their relevance, renown for applying appropriate statistical methods, and impact on the field of study. We believed that, if any problematic methods were observed in these outlets, then they would be even more so widespread in the study of tourism and hospitality. Likewise, we believed that reviewing these journals would cause researchers to take larger notice of our results, given widespread interest in these outlets. It is not guaranteed that publications within other tourism and hospitality outlets follow the same trends as these journals, and typical methodological approaches may differ between outlets. For this reason, future researchers should consider performing similar reviews of EFA in other tourism and hospitality outlets to ensure the robustness of our findings, similar to performing a replication study.

We followed best practices for performing a literature review, such as meeting interrater agreement standards (Aguinis et al., 2020), but literature reviews inherently include subjective elements. We provide our original dataset in Supplemental Material A, and we conducted multiple sensitivity analyses provided in Supplemental Materials B, C, and D. Future researchers can inspect our coding results to ensure that they align with broader understandings of EFA, and they can code the studies themselves to see whether our results replicate when coded by other researchers. Likewise, they can inspect our sensitivity analyses to observe the extent that our coding decisions may have swayed results, which we believe were minimal because our interpretations did not differ between our primary and sensitivity analyses.

Lastly, our intent was to provide a broad overview of EFA in tourism and hospitality research. We provided analyses separated by research domain to provide more nuanced analyses of particular content areas; however, researchers may also be interested in EFA practices regarding specific constructs. For this reason, the current article also provides the constructs studied via each EFA in Supplemental Material A. Readers can search our literature review database for all EFAs conducted on their construct(s) of interest and determine whether practices were appropriate for studying their respective scales. It is possible that many popular constructs (e.g., destination image, place attachment, job satisfaction, and behavioral intent to use specific technologies) have solely been investigated using substandard EFA practices, and a valuable future direction for research could be the reanalysis of these scales using more appropriate practices. Therefore, future research should consider more specific investigations into specific constructs in need of investigation uncovered by our literature review.

6. Conclusion

We reviewed the use of EFA in tourism and hospitality, identifying both positive and negative aspects of the current literature. We were able to provide recommendations as well as standards that future researchers should use when conducting their EFAs, such as criteria for factor loadings. Our results also provided strong evidence that Harman's one-factor test provides few assurances regarding method bias, identifying an area for future quantitative-oriented tourism and hospitality researchers to contribute. Therefore, the current review was able to provide suggestions for both the application and study of EFA.

CRediT authorship contribution statement

Matt C. Howard: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jennifer Henderson:** Writing – review & editing, Validation, Project administration, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset is provided as Supplemental Material A.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.113328.

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Dr. Matt C Howard is an associate professor in the Mitchell College of Business at the University of South Alabama. His research interests span (1) statistics and methodology, (2) health and well-being, (3) individual differences, as well as (4) technology-enhanced training and development. He has published in an array of premier outlets across multiple fields of study, including *Journal of Applied Psychology, Organizational Research Methods, Journal of Organizational Behavior, Journal of Business Research, Information & Management, Human-Computer Interaction, Computers & Education,* as well as *Computers in Human Behavior.* He was also selected as a 2022 Association for Psychological Science Rising Star. His articles can be found on his academic website, www.MattCHoward.com.

Jennifer Henderson is a PhD candidate in the Mitchell College of Business at the University of South Alabama. Her research interests include (1) supply chain management, (2) sustainability, and (3) consumer behavior. She was awarded the Best Paper in the Business-to-Business track as well as the Steven J. Shaw & Joe Hair Overall Conference Best Paper award at the 2020 Society of Marketing Advances (SMA) annual conference. She can be reached at jhenderson@jagmail.southalabama.edu.