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# Use of Location-Based Applications in Hotel and Restaurant Selection: Scale Development and Validation

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## Abstract
Hotel industry is revolutionized especially after the COVID-19 pandemic outbreak. The location-based applications (LBAs) increasingly mediate hotel and restaurant selection by combining location-relevant search, contextual promotions, and consumer-generated evaluations. Prior research has explored location-based service adoption and hospitality booking behaviour, while less attention has been given to whether this distinct information sources can be measured reliably within a common hotel-and-restaurant selection context. This study evaluates and refines three proposed reflective scales: Information Quality (IQ), Contextual Offers and Promotions (COP), and electronic Word of Mouth (EWM). We analyzed survey responses from 436 participants using confirmatory factor analysis for ordinal indicators with weighted least squares mean- and variance-adjusted (WLSMV) estimation. We used the lavaan package in R to test the three-factor model, which was developed from a 10-item scale by removing IQ4 and COP2 based on their factor loadings. The final model consisted of standardized loadings ranging from 0.731 to 0.817, Cronbach's alpha from 0.755 to 0.818, composite reliability from 0.732 to 0.810 and average variance extracted from 0.558 to 0.606. HTMT values ranged from 0.7386 to 0.8435, remaining below the conservative 0.85 criterion. Scaled CFI (0.977), scaled TLI (0.968), and SRMR (0.038) were favourable, whereas robust RMSEA (0.095) indicated remaining approximate misfit. The findings provide preliminary support for internal consistency, convergent validity, and discriminant validity, while also indicating the need for independent-sample confirmation, broader content validation, and criterion and nomological validation.

***Keywords:*** *Location-based applications; Hospitality; Hotel and restaurant selection; Information quality; Contextual offers and promotions; Electronic Word of mouth; Scale validation; Confirmatory Factor Analysis*

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## 1. Introduction
Technology is the gift to businesses offering various competitive advantages such as automation, integration, customization etc. The location-based applications are playing a crucial role to link consumers and hospitality services. These geolocation-based applications seamlessly connect digital information with a user's current location and provide them with the location relevant search results. For example, through these applications consumer can discover nearby hotels and restaurants, get relevant details such as location-aware recommendations, geofenced or proximity-sensitive deals, assist with navigation, and facilitate booking processes. These application's main function lies in streamlining the search process and presenting options that are more relevant to the user's context. The impact of location-based services plays a very important role during the initial phase of the consumer decision-making process. Various studies have revealed that factors such as ranking position, price, and search refinement significantly influence click-through behavior. Users of mobile interfaces tend to prioritize highly ranked options (Gao & Zhan, 2023; Gao et al., 2024). Moreover, location-based retrieval can redistribute visibility across various hospitality providers. Consequently, the information that consumers encounter is influenced by platform


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design and geographic retrieval logic rather than solely by the underlying service quality (Banerjee et al., 2020). In geographically targeted marketing, distance and local competition can impact different stages of the response funnel in varying ways. This pattern underscores the fact that proximity alone is not a straightforward or universal predictor of conversion (Ho et al., 2020). Consumers are more likely to accept personalized recommendations that align with their preferences and their current location (Ho, 2012). When booking a hotel, consumers often prioritize reviews, trust, and price-related evaluations as key factors influencing their decision-making (Ikhsan et al., 2022; Sparks & Browning, 2011; Ladhari & Michaud, 2015). However, location tracking introduces a trade-off between privacy and utility. While services perceived as useful and trustworthy can enhance user adoption, concerns about privacy can deter individuals from using location-aware services (Kim et al., 2017; Xu et al., 2011; Lei et al., 2022). Consequently, even if an application effectively highlights nearby options, it may still struggle to facilitate user selection due to insufficient information, promotional content that doesn't align with user needs, or questionable credibility of social evidence.

The available evidence also varies between hotels and restaurants. Hotel studies show a more direct link between mobile search, reviews, trust, and platform exposure and subsequent clicks, booking intentions, and certain conversion outcomes (Chiu et al., 2022; Debasa et al., 2023; Park & Kim, 2024). In contrast, research on restaurants provides stronger evidence regarding aspects such as discovery, recommendation quality, convenience, check-ins, and user engagement (Chiu et al., 2022; Debasa et al., 2023; Park & Kim, 2024). However, the evidence regarding the incremental impact of location-aware features on completed reservations is less robust (Chiu et al., 2022; Debasa et al., 2023; Park & Kim, 2024). This distinction is crucial for measurement purposes. The present study focuses on consumers' evaluations of information and cues encountered while selecting hotels and restaurants, emphasizing that favorable evaluations don't automatically lead to completed bookings. Despite growing research on location-based hospitality behavior, evidence remains fragmented across various aspects such as application acceptance, search and ranking, personalized marketing, online reviews, privacy, and booking outcomes. However, there's a lack of evidence to suggest that these domains have been jointly validated as a concise measurement instrument. This gap is particularly relevant to hotel and restaurant selection. In this study, we evaluate three proposed reflective constructs: Information Quality (IQ), Contextual Offers and Promotions (COP), and electronic Word of Mouth (EWM). We analyze survey data from 436 respondents to assess item performance, internal consistency, factorial structure, convergent validity, and discriminant validity. Additionally, we refine the initial item set based on the measurement results, which indicate a need for improvement. Our primary contribution lies in the measurement aspect, as we aim to determine whether the three proposed domains can form reliable and empirically distinguishable scales in the context of location-based hotel and restaurant selection.

## 2. Literature Review

### 2.1 Location-based applications and hospitality selection

Location-based services (LBS) leverage geographic context to customize search results, recommendations, navigation, promotions, and other digital content. In the hospitality industry, the relevant location could be the user's real-time position or a destination they've already chosen. This broader interpretation is crucial because both consumers searching for a hotel in a planned destination and those looking for a nearby restaurant depend on spatial relevance, even when the application doesn't continuously track their device.

Technology acceptance and value perspectives provide insights into why such applications impact consumer choices. Perceived usefulness and ease of use are fundamental determinants of technology acceptance (Davis, 1989), while broader acceptance models emphasize performance expectancy, effort, and social influence (Venkatesh et al., 2003). In location-based mobile services, perceived value also depends on the context. Convenience and contextual fit can be important because these services are most useful when they address immediate, place-specific problems (Pura, 2005). Simultaneously, location-


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aware personalization introduces a privacy calculus where consumers weigh relevance and convenience against the perceived cost of disclosure or tracking (Xu et al., 2009; Xu et al., 2011).

Mobile interfaces within hotel searches can influence consumer attention before they even evaluate the property itself. Studies by Gao and Zhan (2023) and Gao et al. (2024) reveal that mobile click-through decisions are influenced by ranking and interface-related search behaviors. Banerjee et al. (2020) further demonstrate that 'near me' retrieval can lead to exposure disparities, meaning that geographic ranking can alter the consideration set presented to the user. Ho et al. (2020) show that distance and local competition can affect consumer responses differently across a geofencing funnel. Location-aware food recommendation systems combine geographic information with preference signals to identify suitable restaurants (Chiu et al., 2022). Meanwhile, digitally accessible reservation systems can change how restaurant locations are discovered and compared (Park & Kim, 2024). However, Debasa et al. (2023) show that perceived usefulness of restaurant reservation applications doesn't always translate directly into a favorable attitude toward use.

**2.2 Information Quality**

Information Quality (IQ) is conceptualized in this study as the perceived accuracy, currency, relevance, and adequacy of information provided by applications for evaluating hotels and restaurants. Location-based decision-making amplifies the significance of these attributes because the usefulness of a search result hinges not only on its general correctness but also on its alignment with the user's current or searched location. The existing literature also distinguishes information quality from the functional operation of an application. Lin et al. (2016) linked information quality with satisfaction in tourism guide cloud services while treating information quality and function quality as separate dimensions. This distinction is relevant to the present study. IQ1 addresses accuracy and currency, IQ3 addresses location relevance, and IQ4 addresses the level of detail. IQ2, which focuses on ease of navigating the application and finding needed information, extends the domain toward information accessibility and may conceptually border on usability or system quality.

**2.3 Contextual Offers and Promotions**

Contextual Offers and Promotions (COP) refers to the perceived relevance, personalization, timing, and decision value of commercial offers or recommendations delivered in relation to a user's location and preferences. Location-linked marketing can reduce search costs when promotions are relevant to the immediate context, but location alone doesn't guarantee a positive response. Ho (2012) found that mobile services tailored to both location and individual preferences increased users' intention to use, highlighting the importance of contextual fit rather than proximity alone. Ho et al. (2020) further demonstrated that distance and local competition influence responses to mobile geofencing, suggesting that the effectiveness of location-targeted communication depends on the consumer's position in the response process.

Schwipper et al. (2020) identified monetary benefits, assistance, enjoyment, and irritation as components of users' evaluations of mobile location-based services, while Bernritter et al. (2021) showed that response to location-based mobile marketing depends on factors like targeting location, product involvement, promotion type, and consumer reactance. These findings align with the privacy-personalization literature, which suggests that while highly tailored offers may be useful, they can also make users more aware of location information being inferred or collected (Xu et al., 2011). The initial COP item pool encompasses several aspects of this construct: location-relevant deals and discounts (COP1), appropriateness of timing and place (COP2), personalized recommendations (COP3), and the extent to which offers enhance the application's value for choosing hotels and restaurants (COP4).

**2.4 Electronic Word of Mouth (EWM)**

Electronic word of mouth (eWOM), as defined in this instrument, refers to consumer-generated evaluations that other users encounter through ratings, reviews, and related platform content. In the hospitality industry, eWOM holds particular significance because the quality of a service or product cannot be fully assessed before consumption. Consequently, ratings and reviews serve as valuable informational


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and social cues that can alleviate uncertainty, foster trust, and influence the alternatives that remain in a consumer's consideration set. Hotel research provides compelling evidence supporting this mechanism. Sparks and Browning (2011) demonstrated that online reviews have a direct impact on hotel booking intentions and perceptions of trust. Similarly, Ladhari and Michaud (2015) established a link between eWOM and booking intentions, attitudes, trust, and website perceptions. More recent research involving hotel apps further illustrates that online reviews work in conjunction with rational price considerations and app trust to explain reservation intentions (Ikhsan et al., 2022). The existing literature consistently aligns with this pattern. Gellerstedt and Arvemo (2019) found that the direction of hotel reviews influences booking intentions and revealed that advice from a close personal source can outweigh the majority opinion expressed in online reviews. Therefore, eWOM should be understood as a perceived decision input rather than an automatically decisive cue. The four EWM indicators focus on the reception and utilization of eWOM: the usefulness of ratings and reviews in assessing quality (EWM1), the believability of reviews (EWM2), the influence of other customers' reviews on choice (EWM3), and the significance of the overall rating (EWM4). These indicators do not measure consumers' intentions to create, post, or share reviews.

## 3. Methodology

**3.1 Research design:** The study evaluated the measurement properties of three proposed scales *(See Annexure-I)*, designated IQ, COP, and EWM, using survey data from 436 respondents. The analysis examined item performance, internal consistency, factorial structure, convergent validity, and discriminant validity. An initial 12-item measurement model was assessed and subsequently refined to a 10-item model. The present analysis addressed the quantitative evaluation and refinement of the proposed measures within one sample.

**3.2. Construct operationalization and questionnaire development:** The initial measurement instrument included four indicators for each construct: IQ1–IQ4, COP1–COP4, and EWM1–EWM4. Responses were recorded using five categories coded from 1 to 5. Each construct was specified as a reflective latent variable, with the corresponding indicators treated as manifestations of the underlying construct. No reverse scoring was applied in the reported analysis. Interpretation therefore assumes that all indicators were coded in the intended direction. The scoring direction and the reflective specification require confirmation against the construct definitions and questionnaire.

**3.3. Sample and data collection:** The analytical dataset comprised 436 respondents. The questionnaire included demographic information, questions on restaurant and hotel applications, and the focal scale items. The survey responses were collected from Pune City, where consumers used location-based applications to book restaurants and hotels. The survey was conducted between May and September 2026. Data were collected via Google Forms using a snowball sampling method. The sample included 282 male respondents (64.7%) and 154 female respondents (35.3%). Respondents aged 18–24 years constituted the largest group (71.6%). Most participants reported graduate or postgraduate qualifications. Table 1 presents the sample characteristics.

Table 1. Respondent characteristics

| *Characteristic* | *Category* | *n* | *%* |
|---|---|---|---|
| *Gender* | Male | 282 | 64.7 |
| | Female | 154 | 35.3 |
| *Age* | 18–24 years | 312 | 71.6 |
| | 25–34 years | 79 | 18.1 |
| | 35–44 years | 20 | 4.6 |
| | 45–54 years | 13 | 3.0 |
| | 55 years and above | 12 | 2.8 |
| *Education* | Up to HSC | 5 | 1.1 |
| | Graduate | 242 | 55.5 |


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| | | | |
|---|---|---|---|
| | Postgraduate | 174 | 39.9 |
| | Doctorate or professional | 15 | 3.4 |

### 3.4. Data preparation

The 12 focal indicators were examined for missing responses and values outside the expected 1–5 range. All 436 records contained complete responses within this range. Consequently, neither missing-value imputation nor case deletion for missing focal-item responses was required. The subsequent removal of indicators affected the measurement specification rather than the number of respondents. Both the initial and revised models were estimated using the same 436 cases. The original data and initial model were retained for comparison.

### 3.5. Measurement-model assessment

Analyses were conducted in R using the psych, lavaan, and semTools packages. Confirmatory factor analysis specified three correlated factors, with each indicator loading on its designated construct. Cross-loadings and residual covariances were fixed to zero. Latent variances were fixed to one for identification. After inspection of the initial model, a standardised loading threshold of 0.70 was adopted for empirical item refinement. Indicators below this threshold were excluded, and the revised measurement model was estimated again. Because this decision followed examination of the initial results, the refinement was treated as a post hoc procedure within the same sample.

Global model fit was assessed using the adjusted chi-square statistic, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardised root mean square residual (SRMR). Scaled and robust fit indices were reported separately. Internal consistency was assessed using Cronbach's alpha and model-based composite reliability. Composite reliability was estimated for the observed ordinal composite. Convergent validity was evaluated using standardised factor loadings and average variance extracted (AVE). For ordinal indicators, AVE was calculated using polychoric correlations and therefore concerns the underlying latent-response variables. Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations (HTMT). The original arithmetic-mean formulation of HTMT was calculated from absolute polychoric correlations. A point estimate below 0.85 was used as the conservative assessment criterion, following Henseler et al. (2015). A supplementary respondent bootstrap comprising 5,000 resamples was also completed using a fixed random seed of 20260909. Each resample contained 436 respondents drawn with replacement, and the revised item set was held fixed throughout. The primary HTMT assessment reported below is based on the original-sample point estimates.

## 4. Data Analysis

### 4.1. Initial model and item refinement

The initial model included 12 indicators distributed across the three constructs. Standardised loadings ranged from 0.581 to 0.796. Two indicators fell below the adopted 0.70 threshold: IQ4, with a loading of 0.697, and COP2, with a loading of 0.581 *(See Table 2.)*. These indicators were removed in one refinement step. The resulting measurement model retained three IQ indicators, three COP indicators, and four EWM indicators. No additional indicators were removed after re-estimation.

Table 2. Item refinement

| *Construct* | *Initial indicators* | *Removed indicator* | *Initial loading of removed indicator* | *Retained indicators* |
|---|---|---|---|---|
| *IQ* | IQ1–IQ4 | IQ4 | 0.697 | IQ1, IQ2, IQ3 |
| *COP* | COP1–COP4 | COP2 | 0.581 | COP1, COP3, COP4 |
| *EWM* | EWM1–EWM4 | None | — | EWM1, EWM2, EWM3, EWM4 |

IQ4 was only marginally below the adopted threshold. Its exclusion, together with the removal of COP2, represents an empirical refinement decision whose implications for construct coverage require assessment against the item wording and theoretical definitions.


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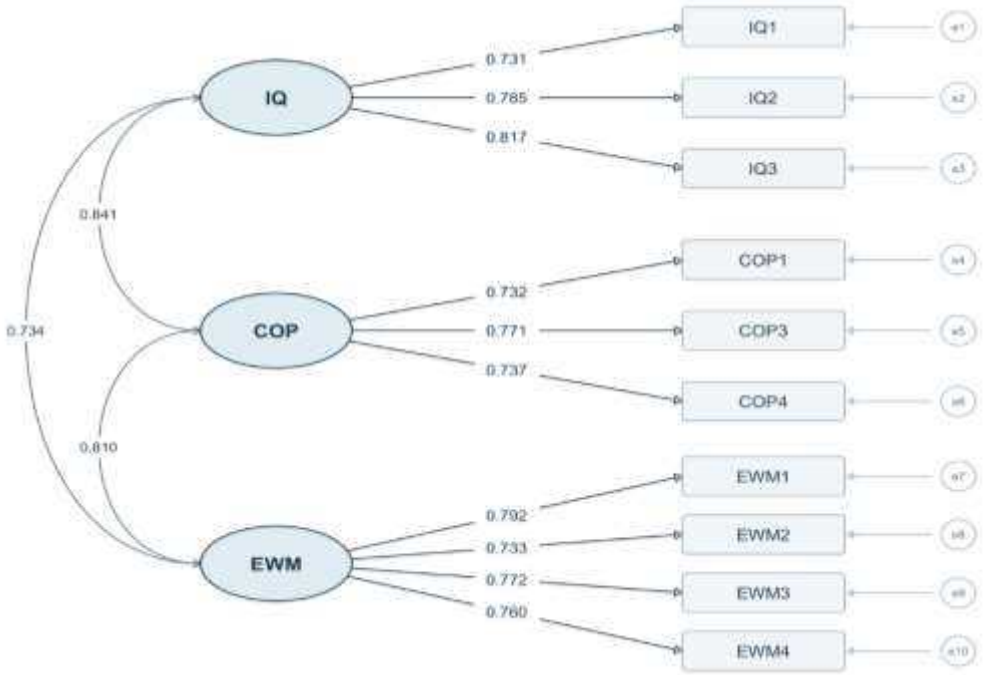
### 4.2. Descriptive statistics and reliability

Composite scores were calculated as the mean of the retained indicators for each construct. IQ had a mean of 3.625 (SD = 0.693), COP had a mean of 3.596 (SD = 0.702), and EWM had a mean of 3.704 (SD = 0.682). Cronbach's alpha was 0.787 for IQ, 0.755 for COP, and 0.818 for EWM. Composite reliability estimates were 0.752, 0.732, and 0.810, respectively. All estimates exceeded the conventional 0.70 benchmark used in the reference scale-development study, supporting internal consistency within the revised scales.

Table 3. Descriptive statistics, reliability, and convergent validity

| *Construct* | *Items* | *Mean* | *SD* | *Cronbach's α* | *Composite reliability* | *AVE* |
|---|---|---|---|---|---|---|
| *IQ* | 3 | 3.625 | 0.693 | 0.787 | 0.752 | 0.606 |
| *COP* | 3 | 3.596 | 0.702 | 0.755 | 0.732 | 0.558 |
| *EWM* | 4 | 3.704 | 0.682 | 0.818 | 0.810 | 0.584 |

### 4.3. Confirmatory Factor Analysis




The revised three-factor model converged and passed the software's post-estimation admissibility check. All retained indicators had standardized loadings above 0.70, ranging from 0.731 to 0.817.

Table 4. Standardized loadings for the revised model

| *Construct* | *Indicator* | *Standardized loading* |
|---|---|---|
| *IQ* | IQ1 | 0.731 |
| | IQ2 | 0.785 |
| | IQ3 | 0.817 |
| *COP* | COP1 | 0.732 |
| | COP3 | 0.771 |
| | COP4 | 0.737 |
| *EWM* | EWM1 | 0.792 |
| | EWM2 | 0.733 |
| | EWM3 | 0.772 |
| | EWM4 | 0.760 |


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The revised model produced an adjusted chi-square statistic of $\chi^2(32) = 126.224$, $p < .001$. Scaled CFI and TLI were 0.977 and 0.968, respectively, and scaled RMSEA was 0.082. Robust CFI was 0.943, robust TLI was 0.920, and robust RMSEA was 0.095, with a 90% confidence interval of [0.080, 0.111]. SRMR was 0.038.

Table 5. Fit indices for the initial and revised models

| *Fit index* | *Initial 12-item model* | *Revised 10-item model* |
|---|---|---|
| *Adjusted $\chi^2$* | 212.752 | 126.224 |
| *Degrees of freedom* | 51 | 32 |
| *p-value* | < .001 | < .001 |
| *Scaled CFI* | 0.967 | 0.977 |
| *Scaled TLI* | 0.957 | 0.968 |
| *Scaled RMSEA* | 0.085 | 0.082 |
| *Robust CFI* | 0.919 | 0.943 |
| *Robust TLI* | 0.896 | 0.920 |
| *Robust RMSEA* | 0.098 | 0.095 |
| *SRMR* | 0.044 | 0.038 |

The revised model showed more favourable fit indices than the initial model. Nevertheless, the robust RMSEA indicated remaining approximate misfit, so the evidence did not support describing global fit as uniformly good. Because the models contained different observed indicators, their fit statistics were compared descriptively rather than through a conventional nested chi-square difference test.

### 4.4. Convergent Validity

AVE was 0.606 for IQ, 0.558 for COP, and 0.584 for EWM. All three values exceeded the conventional 0.50 benchmark. Together with standardized loadings above 0.70, these results supported convergence among the indicators assigned to each construct. The AVE estimates indicate that the specified factors accounted for more than half of the aggregate variance in their underlying item responses. This evidence should be interpreted alongside global model fit, since satisfactory loadings and AVE values do not independently establish that the complete measurement structure is correctly specified.

### 4.5. Discriminant Validity

Discriminant validity was assessed using HTMT point estimates for the revised scales. HTMT was 0.8435 for IQ–COP, 0.7386 for IQ–EWM, and 0.8120 for COP–EWM. All values were below the conservative threshold of 0.85.

Table 6. HTMT Assessment

| *Construct pair* | *HTMT* | *Point estimate below 0.85* |
|---|---|---|
| *IQ–COP* | 0.8435 | Yes |
| *IQ–EWM* | 0.7386 | Yes |
| *COP–EWM* | 0.8120 | Yes |

These findings supported discriminant validity under the HTMT point-estimate criterion. IQ–COP exhibited the greatest overlap and was close to the adopted threshold. IQ–EWM had the lowest HTMT value. All 5,000 supplementary bootstrap resamples produced valid estimates, with no recorded warnings or failures. The threshold assessment in Table 6 refers specifically to the original-sample HTMT values and does not constitute a confidence-interval-based conclusion.

### 4.6. Summary of measurement assessment

The revised instrument comprised 10 indicators measuring three correlated constructs. Reliability estimates exceeded 0.70, all standardized loadings exceeded 0.70, AVE exceeded 0.50, and HTMT point estimates were below 0.85. These findings provided preliminary support for the reliability, convergent validity, and discriminant validity of the revised measures under the stated criteria. The remaining global-


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fit concerns and the use of the same sample for item refinement and re-estimation limit the strength of the validation claim. The revised scales require confirmation of their conceptual coverage and evaluation in an independent sample before they can be presented as comprehensively validated instruments.

## 5. Discussion

The objective of this study was to assess whether Information Quality, Contextual Offers and Promotions, and electronic Word of Mouth could be reliably and empirically distinguished as distinct dimensions of consumer evaluation in location-based hotel and restaurant applications. The revised 10-item model offers preliminary support for this three-factor structure. All retained standardized loadings exceeded 0.70, internal consistency estimates exceeded 0.70, Average Variance Extracted (AVE) exceeded 0.50 for each construct, and all HTMT point estimates remained below the conservative 0.85 criterion. These findings suggest that the retained indicators generally aligned with their intended constructs while maintaining sufficient separation to justify treating Information Quality, Contextual Offers and Promotions, and electronic Word of Mouth as related yet distinct dimensions.

### 5.1 Interpreting the item-refinement results

The item-refinement process demands a more nuanced interpretation than a simplistic 'improvement' narrative. IQ4 initially had a loading of 0.697, just below the adopted 0.70 rule, while COP2 had a significantly lower loading of 0.581. After removing the two items, the Average Variance Extraction (AVE) increased for both IQ and COP, but composite reliability decreased from 0.787 to 0.752 for IQ and from 0.760 to 0.732 for COP. Consequently, the shorter scales improved average variance extraction but compromised some reliability and content breadth. This pattern underscores the importance of a loading threshold guiding, rather than mechanically determining, item deletion during scale refinement. Furthermore, the conceptual cost of the removals is unequal. IQ4 represented the level of detail provided by the application. Its near-threshold loading suggests that future research should consider revising and retesting the wording rather than assuming that information detail is irrelevant to the construct. COP2, on the other hand, is more consequential for content coverage because it was the only item that explicitly captured receiving an offer at the right time and place. The literature on location personalization and geofencing emphasizes contextual fit, proximity, and situational relevance (Ho, 2012; Ho et al., 2020).

### 5.2 Model fit and discriminant validity

The model-fit evidence is favourable on several indices but not uniformly strong. Scaled CFI and TLI were 0.977 and 0.968, respectively, and SRMR was 0.038, while robust CFI and TLI were 0.943 and 0.920. In contrast, robust RMSEA was 0.095 with a 90% confidence interval of [0.080, 0.111]. The revised model should therefore not be described as demonstrating unequivocally excellent fit. The mixed pattern is more appropriately interpreted as support for the proposed structure accompanied by remaining approximate misfit that warrants replication and further specification testing. Discriminant validity shows a similar combination of support and caution. The IQ-COP HTMT estimate of 0.8435 was below the 0.85 criterion but close to it, whereas IQ-EWM (0.7386) and COP-EWM (0.8120) showed greater separation. The comparatively high IQ-COP relationship is conceptually understandable because a location-relevant promotion is still information presented by the application and may be evaluated partly through relevance and clarity. The result supports retaining separate constructs at this stage, but it also indicates that future item wording should sharpen the distinction between the quality of general application information and the contextual value of explicitly commercial offers.

### 5.3 Theoretical and practical implications

Theoretically, the study shifts attention from treating location-based application use as a single acceptance judgement to examining distinct evaluative inputs within the decision environment. Separating application-provided information, contextual commercial stimuli, and consumer-generated social evidence provides a more granular measurement basis for future models of hospitality choice. The present results are preliminary rather than definitive, but they indicate that these domains can be modelled separately without requiring them to be statistically independent. Practically, the revised scales can serve


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as a diagnostic instrument for researchers and, after further validation, for app or platform managers. Low IQ scores would indicate problems with accuracy, relevance, or accessibility of information; low COP scores would point to weak contextual fit or value of offers; and low EWM scores would indicate limited credibility or decision usefulness of ratings and reviews.

### 5.4 Limitations and directions for further validation

Several limitations constrain the strength of the validation claim. First, item refinement and re-estimation were conducted in the same sample, so the revised model has not been independently cross-validated. Second, the sample is demographically uneven: 71.6% of respondents were aged 18-24 years and 64.7% were male, which limits the basis for assuming stable measurement across age and gender groups. Third, the present analysis combines hotel and restaurant application contexts without demonstrating measurement invariance across them. Fourth, the study evaluates reliability and factorial validity but does not establish criterion validity, nomological validity, predictive validity, or relationships with actual booking behaviour. A further limitation concerns construct content and item provenance. The current manuscript must document whether the items were newly developed or adapted, how they were generated, and how expert or respondent feedback established face and content validity. Future scale development should therefore include explicit content-validation procedures, cognitive pretesting, and independent-sample confirmation of the revised item set.

## 6. Conclusion

This study provides preliminary evidence for a concise three-factor measurement structure capturing Information Quality, Contextual Offers and Promotions, and electronic Word of Mouth in the context of location-based hotel and restaurant selection. The revised 10-item model demonstrated acceptable internal-consistency estimates, standardized loadings above 0.70, AVE above 0.50, and HTMT point estimates below 0.85. These results support the interpretation of the three constructs as related but empirically distinguishable dimensions of consumer evaluation. The evidence nevertheless supports refinement rather than a claim of comprehensive scale validation. Robust RMSEA indicated remaining model misfit, IQ-COP discriminant validity was close to the conservative threshold, and two item deletions narrowed construct coverage. Most importantly, the revised model was derived and re-estimated in the same sample and has not yet been tested against external criteria or behavioural outcomes. The scale should therefore be treated as a promising measurement instrument for further validation. Independent replication, stronger documentation of item development and content validity, sector-specific invariance testing, and subsequent nomological and predictive assessment are required before it is presented as a fully validated measure of consumer perceptions of location-based hospitality applications.

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**Annexure- I**

| *Factor / Construct* | *Code* | *Questionnaire item* |
|---|---|---|
| *Information Quality (IQ)* | IQ1 | These apps provide accurate and up-to-date information about hotels and restaurants near my chosen location. |
| | IQ2 | It is easy to navigate these apps and find the hotel or restaurant information I need. |
| | IQ3 | These apps show me relevant results based on my location or the location I search. |
| *Contextual Offers and Promotions (COP)* | COP1 | These apps show me deals and discounts relevant to my location. |
| | COP2 | I receive offers at the right time and place |
| | COP3 | The recommendations I receive are personalized to my preferences. |
| *E-Word of Mouth (EWM)* | EWM1 | Ratings and reviews on these apps help me judge the quality of a hotel or restaurant. |
| | EWM2 | I find the reviews on these apps believable. |
| | EWM3 | Reviews from other customers strongly influence which hotel or restaurant I choose. |
| | EWM4 | The overall rating of a hotel or restaurant matters when I make my choice. |


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