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# Formative & Reflective Measurement Models

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## Abstract

This research paper explores the distinctions between reflective and formative measurement models—the two commonly used methodologies in social science research for measuring latent variables. Reflective models believe that a latent variable causes its indicators, whereas formative models see the indicators contributing to the latent variable. The paper explores the theoretical foundations of both models with a specific focus on their applicability in business disciplines such as marketing, management, and organizational behavior. Business-relevant constructs—such as brand equity, customer satisfaction, leadership effectiveness, and employee engagement—are highlighted to demonstrate the practical implications of model selection. In addition, the research paper analyzes how these two models help define relationships in observable variables and latent variables, such as the nature of the construct, causality, and the type of indicators. The research paper also focuses on the statistical approaches used to evaluate both models, including factor analysis, structural equation modeling, path analysis, etc. The paper will help researchers identify measurement models to improve the insights in determining the model relationship among measurable and latent variables, and ways to define construct validity and related phenomena.

**Keywords**: Formative Model, Reflective Model, Latent Variable, Social Science Research, Measurable or observable variable.

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## 1. Introduction

Management researchers use two primary measurement models, i.e., formative and reflective, for defining strategic models that establish relationships between constructs or concepts and their measurable variables, indicators, or items. Psychology, management, and marketing literature increasingly emphasizes formative measurement models for operationalizing latent variables, reflecting an evolving understanding of measurement models. In marketing, brand equity or customer loyalty constructs may be multidimensional and better modeled formatively because their indicators (e.g., perceived quality, brand associations, and loyalty) are not always interchangeable (Rossiter, 2002; Finn & Kayande, 2005). In psychology, attitudes or emotional states are frequently measured reflectively, but complex psychological constructs such as resilience or well-being, which are multidimensional and causative indicators, may necessitate formative modeling (Borsboom et al., 2003; Sharma, 2022). Employee engagement, leadership effectiveness, and organizational performance are increasingly recognized as formative constructs in management and organizational behavior because they are based on job satisfaction, autonomy, and goal clarity (MacKenzie et al., 2011; Petter et al., 2007).
Constructs, also called latent variables, are unobservable phenomena such as attitudes, perceptions, or beliefs that act as "verbal surrogates" for the realities they represent (Edwards & Bagozzi, 2000). These constructs are quantified through observable measures collected via self-reporting, interviews, or observations (Chin, 1998). Statistical covariance or correlation is commonly employed to link unobserved constructs with their observable variables, emphasizing the importance of distinguishing between these measurement approaches to assign meaningful links in structural models.

Over the past few decades, research on structural equation modeling (SEM) and construct validity has changed tremendously. A solid theoretical foundation was established by the foundational works of academics such as Edwards & Bagozzi (2000), DeVellis (1991), and Blalock (1982). However, more recent contributions have significantly improved the field. For example, MacKenzie, Podsakoff, & Podsakoff (2011) and Podsakoff et al. (2012) thoroughly discuss construct measurement, tackling the ongoing difficulties in model specification and construct validity. Despite these advances, the argument over the best methods for demonstrating construct validity continues (e.g., Petter, Straub, & Rai, 2007; Hair et al., 2019). Scholars are increasingly emphasizing the necessity of distinguishing between reflective and formative measurement models, claiming that wrong model specification can jeopardize structural validity (e.g., Becker, Klein, & Wetzels, 2012)
Diamantopoulos and Siguaw (2006), as well as Sarstedt et al. (2016), enhanced the debate in marketing and information systems research by demonstrating how formative measurement models can more effectively represent specific constructs. Wilcox et al. (2008) and Rossiter (2011) critique the misuse of reflective models and argue for contextualized operationalization, particularly when conceptions are composite or behaviorally driven. The appropriate link between constructs and indicators is critical. Reflective models presume that the latent construct produces the observed indicators, also known as effect indicators (Bollen & Diamantopoulos, 2017). These indicators are highly connected and interchangeable without significantly affecting the construct's meaning (Jarvis, MacKenzie, & Podsakoff, 2003). For example, Perceived ease of Use, which was first proposed by Davis (1989), is often modeled reflectively using indicators such as "ease of learning" and "controllability," which are assumed to co-vary as expressions of the latent construct.
In contrast, formative indicators are not meant to be connected; instead, they define or shape the construct. Incorrectly characterizing such constructs as reflective can lead to significant specification errors, compromising measurement validity and causal inference in structural models (Hair, Hult Ringle & Sarstedt 2021).
These ongoing arguments highlight the need for theoretically grounded model specifications. According

to Henseler (2017) and Sarstedt, Hair, Cheah, Becker, and Ringle (2019), the construct's conceptual structure, study objectives, and empirical data features must all be considered when deciding between reflective and formative indicators.

## 2. Research Objectives

The ultimate objective of this research paper is to distinguish between formative and reflective measurement models and to determine the evaluation thresholds required for each. This study incorporates the mathematical underpinnings of both models, offering comprehensive knowledge that serves as the foundation for the research paper's approach and evaluation.

## 3. Research Methodologies

It is based on reviewing past and recent literature to investigate the concepts and frameworks of formative and reflective measuring methods. The research technique is based on the systematic review of published literature on these models, emphasizing their mathematical foundations, assessment criteria, and practical applications. The research paper seeks to clarify the differences between formative and reflective indicator measurement models by integrating views from various scholarly sources. This literature review provides a basis for understanding the theoretical and practical consequences of using formative and reflective indicators in empirical research or survey-based research in the future.

## 4. Reflective and Formative Measurement Model

This section presents concepts of formative and reflective models along with a comparison of key facts, followed by a possible explanation of the statement “Are Constructs Inherently Formative or Reflective?”.

### 4.1 Concept of Formative Measurement Model

The formative measurement model can be outlined in the following equation form, which is explained below:

$$\eta = \sum_i \gamma_i X_i + \boldsymbol{\xi}_i$$

i. $\eta$ denotes a latent variable inferred from other variables rather than observed directly.
ii. $\boldsymbol{\sum_i}$ Indicates a summation over all observable variables ($X_1, X_2, X_3, \ldots\ldots, X_n$) included in the equation.
iii. $\boldsymbol{\gamma_i}$ indicates the **coefficients** or **weights** associated with each observed variable ($X_1, X_2, X_3, \ldots\ldots\ldots\ldots X_n$) included in the equation
iv. $X_i$ are the variables that have been observed or are observable. These are the directly measurable factors (such as survey items or test scores) used to estimate the latent variable.
v. $\xi$ i define the disturbance or mistake phrase. This compensates for variability in $\eta$ that cannot be explained by observed factors ($X_1, X_2, X_3, \ldots\ldots\ldots\ldots, X_n$).

The Equation of Formative Measurement Model will follow a pictorial representation in Figure 1.

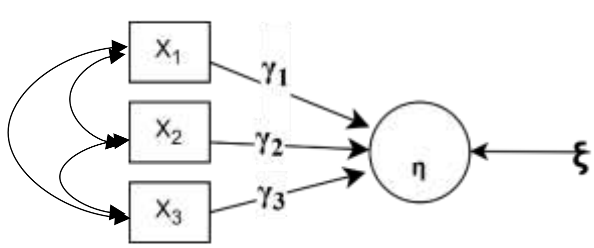

Figure 1. Direct Formative model

**Source: Edwards & Bagozzi (2000); Hanafiah (2020); Podsakoff et al. (2003)**

The direct formative model specifies measures as correlated causes of a construct. This model is depicted in Figure 1, which shows the effects of the $X_i$ measures on the construct $\eta$ . The disturbance term ξ represents that part of the construct $\eta$ that is not explained by the $X_i$, and thus may be interpreted as measurement error. In contrast, the $X_i$ are conceived as error-free causes of $\eta$ (MacCallum and Browne, 1993).

### 4.2 Concept of Reflective Measurement Model

The Reflective Measurement Model can be outlined in the following equation form, which is explained below:

$$X_i = \lambda_i \xi + \delta_i$$

i. $X_i$ denotes an observed indicator or manifest variable that may be directly viewed in data, such as survey responses or test results.
ii. $\boldsymbol{\lambda_i}$ denotes Factor loading. This indicates the strength of the link between the latent construct (ξ) and the observable variable ($X_i$). This indicates how much of the variation in $X_i$ is explained by ξ.
iii. **ξ** denotes latent variable or construct that the observable variables are intended to measure, such as intelligence, satisfaction, or trust.
iv. $\boldsymbol{\delta_i}$ denotes a measurement error or disturbance. This is the variance in the observed variable ($X_i$) that is not explained by the latent construct (ξ) and is due to measurement error and other unknown factors.

The Equation of the Reflective Measurement Model will have a pictorial representation as given in Figure 2.

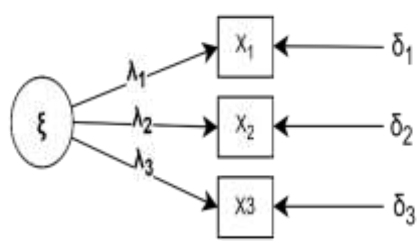


Figure 2. Direct reflective model

**Source: Edwards & Bagozzi (2000); Podsakoff et al. (2017); Hanafiah (2020)**

The direct reflective model specifies the direct effects of a construct on its measures. This model is depicted in Figure 2, in which the construct ξ and the random measurement error $\delta_i$ influence each Xi measure. Hence, variance in each measure is explained by a construct common to all measures and error unique to each measure, and covariation among the measures is attributed to their common cause **ξ (**Edwards & Bagozzi, 2000).

### 4.3. Key Aspects of the Reflective and Formative Measurement Model

This section presents key aspects of reflective and formative models, with a view to comparing the two in Table 1.

**Table1: Key Aspect of Reflective and Formative Measurement Model**

| Sr No. | Aspect | Formative | Reflective | Reference |
|---|---|---|---|---|
| 1 | **Definition** | Indicators represent the underlying unobservable variable. | Indicators represent the underlying unobservable variable. | Weele 2020; *Blotenberg et al. (2022).* |
| 2 | **Mathematical Equation** | $\eta = \sum_i \gamma_i X_i + \xi_i$ | $X_i = \lambda_i \xi + \delta_i$ | Edwards & Bagozzi (2000). |
| 3 | **Assumption** | Indicators are representations of different aspects of the construct. | Indicators are manifestations of a single underlying construct. | Weele (2020) |
| 4. | **Measurement Direction** | Arrows point from the indicator variables to the construct (effect to cause). | Arrows point from the construct to the indicator variables (cause to effect). | Hair et al. (2021) |
| 5. | **Error Term** | The error term is not associated with formative measures. | The error term is associated with each indicator in reflective measures. | Hair et al. (2021) |
| 6. | **Measurement Type** | Typically, multiple indicators are used to measure the latent construct. Indicators are interchangeable, so dropping one indicator should not drastically change the meaning of the construct. | Can use either multiple items or a single item for measurement means. Indicators are not interchangeable; each indicator captures a unique part of the construct. Removing an indicator could change the meaning of the construct. | Blotenberg et al. (2022) & Hanafiah, (2020) |

### 4.4. Are Constructs Inherently Formative or Reflective?

No such data is available wherein it is verified that all constructs are inherently formative and reflective. However, many researchers mention that reflective measurement models are more prevalent and tools such as structural equation modeling (SEM) or partial least squares- structural equation modeling (PLS - SEM) are more common approaches (Hair, et al., 2017a; Sarstedt, et al.,.2021; Chin & Newsted,1999). However, researchers also mentioned, "Some constructs are fundamentally formative in nature and should not be modeled reflectively"(Podsakoff et al., 2003).

There is a debate about the social-economic status (SES) construct. Heise (1972) explained that SES is a construct induced from observable variables such as income, education, wealth, and occupational prestige. It has no measurable reality apart from these variables, which appear to be its causes. Therefore, SES is a formative construct.

Kluegel et al. (1977) demonstrated that subjective SES measures can function effectively as reflective indicators. For example, Self-Perceived Social Status. This becomes an additional indicator that contradicts the conceptualization by Heise (1972). Therefore, SES construct may be termed as reflective construct. In addition, the more features relating to nature indicators, such as causal, composite, etc., must be considered. In many cases, this dual nature of constructs highlights the importance of carefully evaluating their characteristics and ensuring that the selected measurement approach aligns with the conceptual and operational definitions.

## 5. Comparative Analysis of Reflective and Formative Measurement Models

The distinction between reflective and formative models has profound implications for research design, particularly in disciplines like information systems, psychology, and marketing. Reflective indicators are prevalent in models where latent constructs such as attitudes or perceptions drive observed behaviors. These models rely on the assumption that indicators are manifestations of the construct. For example, in technology acceptance research, constructs such as Perceived Usefulness or Perceived Ease of Use are typically measured using reflective indicators to validate the latent variables (Davis et al., 1989). Formative models, in contrast, are employed when indicators collectively form a construct, such as socioeconomic status or organizational performance. These indicators represent unique facets of the construct and are not expected to correlate strongly. For example, organizational performance may be formed by indicators like revenue, employee satisfaction, and market share, each contributing distinctively to the overall construct. The comparison is based on theoretical, empirical, and exceptional considerations.

### 5.1 Theoretical considerations

To determine whether an indicator is formative or reflective, researchers consider three aspects: the nature of the construct, the direction of causality between items and the latent construct, and the characteristics of the items used to assess the construct. A summary of these factors is shown below:

#### 5.1.1 Consideration 1- Nature of the construct

In a reflective model, the latent construct exists (absolutely) regardless of the measures (Borsboom et al., 2004; Rossiter, 2002). Reflective scenarios are commonly used to assess attitudes and personality by eliciting reactions to indicators. Almost all scales in business and related methodological literature on scale development (Bearden & Netemeyer,1999; Bruner II et al., 2001; Netemeyer et al., 2003; Spector, 1992) take a reflective measuring process. Venkatesh et al. (2013) discussed that reflective models dominate in studies involving psychological constructs (e.g., user satisfaction), formative models are more suitable for constructs where indicators form the underlying construct. They mention that in information technology adoption and innovation research, formative indicators such as perceived ease of use and perceived usefulness contribute to the overall technology adoption construct.

Borsboom et al. (2003) inferred that a formative model allows the researcher to interpret the latent concept as constructivist, operationalist, or instrumentalist. For example, the human development index (HDI) does not exist as an independent organization. Instead, it is a composite human development indicator that includes health, education, and income (UNDP, 2006). A change in one or more of these components will likely influence a country's HDI score.

#### 5.1.2 Consideration 2- Direction of causality between items and latent construct

The direction of causation between the construct and the indicators is the second most important theoretical issue when determining whether the measurement model is reflecting or formative. Reflective models presume causality from the construct to the indicators. Formative models work in the opposite direction, with causality flowing from the indicators to the construct. Thus, in reflective models, a change in the construct results in a change in the indicators. In the case of formative models, the opposite is true: a change in the indicators leads to a change in the studied construct.

#### 5.1.3 Consideration 3- Characteristics of indicators

The features of the indicators used to quantify latent components vary significantly between reflective and formative settings. In a reflective model, change in the latent variable must occur before variation in the indicator(s). Effect Model (Reflective Indicators) Causal Model (Formal Indicators) Interchangeability allows researchers to measure the construct by picking a few relevant indicators from its domain (Churchill, 1979; Nunnally & Bernstein, 1994). Diamantopoulos & Siguaw (2006) mentioned that in formative constructs, the inclusion or exclusion of specific indicators does not impact the overall content validity of the construct. On the other hand, it will impact in reflective models. They reasoned that formative indicators are appropriate for complex constructs where no single indicator can fully reflect the construct, such as brand equity or socioeconomic status (SES).
However, as Rossiter (2002) points out, this does not imply that we require a census of indicators, as Bollen and Lennox (1991) proposed. As long as the indicators conceptually describe the domain of interest, they can be considered adequate for empirical prediction. Table 2 summarizes the three theoretical considerations shown in Table 2.

**Table 2: A framework for assessing reflective and formative models: Theoretical[1]**

| Sr No. | Basis | Formative | Reflective | Reference |
|---|---|---|---|---|
| | | **Theoretical Considerations** | | |
| 1 | **Nature of construct** | Latent constructs are determined by combining their indicators. Or one can say that the indicators form the latent construct | The **latent construct** causes the indicators. | Borsboom et al. (2003, 2004); Chin (1998) |
| 2 | **Direction of causality between items and latent construct** | Causality from construct to items. Indicators cause the latent variable. Variation in the item measures (indicators) causes variation in the construct. Variation in the construct does not directly affect variation in the item measures because the indicators form the | Causal flow from the latent construct to the indicators. Variation in the construct causes variation in the item measures. | Bollen and Lennox (1991); Edwards and Bagozzi (2000); Rossiter (2002); Jarvis et al. (2003) |

| | | | | |
|---|---|---|---|---|
| | | construct rather than being a reflection of it. | | |
| **3.** | **Characteristics of items used to measure the construct** | Characteristics of items used to measure the construct.<br>Items share a common theme.<br>Items are interchangeable.<br>Adding or dropping an item does not change the conceptual domain of the construct. | Items define the construct.<br>Items need not share a common theme.<br>Items are not interchangeable.<br>Adding or dropping an item may change the conceptual domain of the construct. | Rossiter (2002).<br>Jarvis et al. (2003) |

### 5.2 Empirical considerations

To determine whether an indicator is formative or reflective, researchers consider three aspects: the Item intercorrelation, Item relationships with construct antecedents and consequences, and Measurement error and collinearity of the items used to assess the construct. A summary of these factors is shown below:

#### 5.2.1 Consideration 1: Item intercorrelation

In a reflective model, items are driven by the underlying construct and should have positive and high intercorrelations. In a formative model, items do not necessarily share a common theme, resulting in no preset pattern of intercorrelation. In a formative model, items can have zero, high, or low intercorrelation. Regardless, researchers should ensure that indicator intercorrelations are as expected. Preliminary evaluations of questionnaire items provided by respondents must include these checks. Preliminary analyses include identifying outliers (e.g., using distances in factor spaces for reflective measurement models or regression influence diagnostics for formative models) and ensuring the construct's dimensionality matches the researcher's hypothesis. To ensure validity, use standard factor models or principal components analysis to establish correlations between items and constructs, bivariate correlations, factor or regression analysis, reliability statistics (only for reflective measurement models), and avoid common method bias when multiple constructs are part of a theoretical structure. Preliminary studies and diagnostics can provide insights into indicator intercorrelation and advise which measurement model to utilize. To ensure validity, use standard factor models or principal components analysis to establish correlations between items and constructs, bivariate correlations, factor or regression analysis, reliability statistics (only for reflective measurement models), and avoid common method bias when multiple constructs are part of a theoretical structure. Preliminary studies and diagnostics can provide insights into indicator intercorrelation and advise which measurement model to utilize. However, these findings cannot validate or refute theoretical assumptions about the measurement model. For that, researchers require stronger tests.

Researchers can use statistics like factor loading, communality, Cronbach's alpha, average variance extracted, and internal consistency to evaluate the reliability of reflective indicators (Trochim, 2007). Reliability metrics rely on high intercorrelations among indicators, making them unsuitable for formative indicators that do not make such assumptions. One of the key operational issues in using formative indicators is that no simple, easy, and universally accepted criteria exist for assessing their reliability. In reflective measurement models, observed indicators are expressions of an underlying latent variable, which is predicted to have a strong intercorrelation. In marketing, for example, customer satisfaction is

frequently considered as a reflective concept, with survey items such as "I am happy with the service" or "I would recommend the product" being connected and interchangeable (Jarvis et al., 2003).
In contrast, indicators define the idea in formative models rather than being correlated. Brand equity is an excellent example in business, where variables such as brand awareness, perceived quality, brand connections, and brand loyalty may be conceptually distinct but collectively create the brand equity construct (Bagozzi, 2011).

### 5.2.2 Consideration 2: Item relationships with construct antecedents and consequences

As before, structural equation modeling using the PLS method can help assess criterion validity against two theoretically relevant and independent single-item constructs. A reactive market orientation is linked to increased recurrent business from valuable clients. The quiz assesses the level of recurring business with valuable clients on a 5-point Likert scale, comparing it to the top-performing businesses in the industry. This language helps respondents understand the construct as a concrete, single thing. Therefore, a single-item measure is appropriate (Bergvist & Rossiter, 2007; Rossiter, 2002). The analysis employs reverse scoring, with five indicating "far better". Proactive market orientation is strongly linked to successful revenue generation from new items. The questionnaire assesses income generation success with a similar question: “Compared to the highest performing business in your industry, the level of success generating revenue from new products is far better or much worse.” There should be no substantial associations between the reactive and proactive criteria. The expected correlations between constructs and criterion questions are a good test of the measurement model. Rossiter (2002) and Bergkvist and Rossiter (2007) contend that in business research, single-item criterion constructs (e.g., revenue growth or customer retention) can be used to validate formative constructs when the results are explicit, concrete, and clearly understood by respondents.

### 5.2.3 Consideration 3: Measurement error and collinearity

Evidence suggests that market orientation can be measured in proactive and reactive ways, using distinct constructs. This support is limited to consideration 5, where formative and reflective measurement models align with theoretical predictions. The level of support for conceptualizing and measuring market orientation formatively as a two-dimensional construct has Significant intellectual consequences. Formative models present additional hurdles in terms of measurement inaccuracy and multicollinearity. Because the indicators are not interchangeable, traditional reliability indices such as Cronbach's alpha or composite reliability are inappropriate (Petter et al., 2007). Instead, researchers must use collinearity diagnostics, such as ensuring VIF values are less than 5, to avoid redundancy or estimation bias (Hair et al., 2021).
Most marketing research treats market orientation as a one-dimensional concept, measuring it using a reflecting model. Theoretical and empirical factors suggest that current scales may not be fully valid, supporting the argument for two distinct conceptions. A summary of the above three theoretical considerations is shown below:

**Table 3: A framework for assessing reflective and formative models: Empirical Considerations**

| | | Empirical Considerations | | |
|---|---|---|---|---|
| | | **Formative** | **Reflective** | **References** |
| **1.** | **Item intercorrelation** | Items can have any pattern of intercorrelation but should possess the same | Items should have high positive intercorrelations. Empirical tests: assessing | Cronbach (1951); Nunnally and |

| | | | | |
|---|---|---|---|---|
| | | directional relationship. Empirical test: no empirical assessment of indicator reliability is possible; various preliminary analyses help check the directionality between items and the construct. | internal consistency and reliability by Cronbach's alpha, average variance extracted, and factor loadings (e.g., from standard or confirmatory factor analysis). | Bernstein (1994); Churchill (1979); Diamantopoulos and Siguaw (2006) |
| **2.** | **Item relationships with construct antecedents and consequences** | Items may not have similar significance of relationships with the antecedents/consequences as the construct. Empirical test: Nomological validity can be assessed empirically using a MIMIC model, and/or structural linkage with another criterion variable. | Items have similar signs and significance of relationships with the antecedents/consequences as the construct. Empirical test: content validity is established based on theoretical considerations and assessed empirically via convergent and discriminant validity. | Bollen and Lennox (1991); Diamantopou los and Winklhofer (2001); Diamantopou los and Siguaw (2006) |
| **3.** | **Measurement error and collinearity** | The error term cannot be identified if the formative measurement model is estimated in isolation. Empirical test: the vanishing tetrad test can determine if the formative items behave as predicted. Collinearity should be ruled out by standard diagnostics such as the condition index. | The error term in items can be identified. Empirical test: Standard factor analysis can be used to identify and extract the measurement error. | Bollen an d Ting ( 2000); Diamantopoulos (2006) |

To learn more about formative and reflective models, some further considerations are covered below after discussing various factors based on theoretical and empirical considerations. Indicator correlation, causality, and error handling constitute significant distinctions that help researchers choose models depending on study goals and construct attributes, as shown in Table 3:

**Table 3: Additional Considerations**

| **Aspect** | **Reflective Model** | **Formative Model** | **Citation** |
|---|---|---|---|
| **Causal Priority** | Construct cause indicators | Indicators define the construct | Bollen & Lennox (1991) |

| | | | |
|---|---|---|---|
| **Measurement Error** | Errors are measured at the indicator level | Errors are assessed at the construct level | Diamantopoulos & Winklhofer (2001); Jarvis et al. (2003) |
| **Internal Consistency** | Indicators should be consistent and highly correlated | Internal consistency is not required | Bollen & Lennox (1991); Jarvis et al. (2003) |
| **Correlation Between Indicators** | High correlation is expected | Correlations may vary and are not required | Jarvis et al. (2003) |
| **Identification** | Requires at least three indicators | Requires at least two causal paths and indicators | Bollen & Lennox (1991); Diamantopoulos & Winklhofer (2001) |
| **Error Terms** | Present at the indicator level | Only disturbances are considered at the construct level | Edwards & Bagozzi (2000); Diamantopoulos & Winklhofer (2001) |
| **Interchangeability** | Removing an indicator does not affect the construct | Removing an indicator changes the construct | Jarvis et al. (2003); Nunnally & Bernstein (1994) |
| **Measurement Model Assumption** | Assumes indicators reflect the construct | Assumes indicators form the construct | Diamantopoulos & Winklhofer (2001); Jarvis et al. (2003) |
| **Measurement Model Assessment** | Assessments: Internal consistency reliability, Indicator reliability, Convergent validity, Discriminant validity, Fornell-Larcker criterion, Cross loadings, and Heterotrait-monotrait ratio of correlations (HTMT) | Assessments: Multicollinearity, Construct Validity, and Indicator Reliability | Hanafiah (2020) |

## 6. Measurement Model Assessment

### 6.1 Formative Measurement Model Assessment

Formative measurement specifies that the observable indicators are considered to cause the latent construct. Thus, formative constructs should be assessed based on the statistical significance and size of the indicator weights and collinearity among indicators. For the evaluation of the formative measurement model, this study adopted the guidelines outlined by Specifically, three parameters should be examined: (i) multicollinearity; (ii) construct validity; and (iii) indicator reliability. The criteria for the fit of the formative measurement model are presented in Table 4 below.

**Table 4 Formative Outer Model Assessments**

| Criterion | Recommendations/Rules of thumb /Thresholds | Sources |
|---|---|---|
| **Multicollinearity** | Variance inflation factor (VIF) is used to determine whether there is a high | Hair et al. (2017) |

| | | |
|---|---|---|
| | correlation between the formative indicators. | |
| **Construct Validity** | Estimate the indicator weights to measure each formative indicator's contribution to the latent variable's variance. | Petter et al. (2007) |
| **Indicator Reliability** | Calculates the outer loadings of the formative construct; if the item loadings are relatively high (>.50), the indicator should be retained | Hair et al. (2012) |

Guidelines for assessing formative measurement models in SEM are given in Table 4. In order to identify significant correlations amongst formative indicators and ensure they are not redundant, it suggests using the Variance Inflation Factor (VIF) for multicollinearity (Hair et al., 2017). Estimating the indicator weights to ascertain each indicator's contribution to the latent variable's variance is how construct validity is evaluated (Petter et al.,2007). According to the table, indicators with outer loadings more than 0.50, which show a significant correlation between the indicator and the construct, should be kept for indicator reliability (Hair et al., 2012).

### 6.2 Reflective Measurement Model Assessment

Reflective measurement implies that a latent or unobservable concept causes variation in a set of observable indicators, which therefore can be used to gain an indirect measurement of the concept. In order to examine the reflective measurement models, four parameters were examined: (i) internal consistency reliability, (ii) indicator reliability, (iii) convergent validity, and (iv) discriminant validity. The criteria for the reflective measurement model fitting are presented below in Table 5

**Table 5 Reflective Outer Model Assessments**

| Criterion | Recommendations/Rules of thumb /Thresholds | Sources |
|---|---|---|
| **Internal consistency reliability** | Do not use Cronbach's alpha; composite reliability > 0.70 | Bagozzi and Yi (1988), Hanafiah (2020) |
| **Indicator reliability** | Standardized indicator loadings > 0.70; in exploratory studies, loadings of 0.40 are acceptable | Hulland (1999) |
| **Convergent validity** | Average variance extracted (AVE) > 0.50 | Bagozzi and Yi (1988) |
| **Discriminant validity - Fornell-Larcker criterion** | Each construct's AVE should be higher than its squared correlation with any other construct | Fornell and Larcker (1981) |
| **Cross loadings** | Each indicator should load highest on the construct it is intended to measure | Chin and Newsted (1999) |
| **Heterotrait-monotrait ratio of correlations (HTMT)** | No discriminant validity problems (HTMT>0.85 criteria) | Henseler et al., (2009) |

As per Table 5 above, Internal consistency reliability is one of the key criteria for assessing reflective measuring models in SEM, and this table suggests composite reliability over 0.70 rather than Cronbach's alpha (Bagozzi & Yi, 1988). Standardized loadings > 0.70 are recommended by indicator reliability, but 0.40 is appropriate for exploratory research (Hulland, 1999). An Average Variance Extracted (AVE) of more than 0.50 is necessary for convergent validity (Bagozzi & Yi, 1988). According to the Fornell-Larcker criterion, a construct's AVE should be greater than its squared correlation with any other construct to guarantee discriminant validity (Fornell & Larcker, 1981). According to Chin and Newsted (1999), cross-loadings must demonstrate that each indicator loads most on its intended construct. To ensure no problems with discriminant validity, the Heterotrait-Monotrait ratio (HTMT) should be less than 0.85 (Henseler et al., 2009).

## 7. Conclusion

This research provides insights into the concept of formative and reflective measurement models. This study presents a set of principles for categorizing formative and reflective conceptions, as well as evaluation stages and criteria for the formative and reflective measurement models. Furthermore, this article clearly distinguishes between reflecting and formative constructs, and construct identification and validation depend on the type of construct indicated by the researcher. This work proposes that mathematical equations that confirm the model be presented visually to researchers and that the decision to use a formative or reflective indicator be made on theoretical grounds.

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