Intrinsic and Extrinsic Motivation for University Staff Satisfaction: Confirmatory Composite Analysis and Confirmatory Factor Analysis

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Abstract

The hierarchical construction model (HCM) may be used to minimize colinear formative indicators while increasing the statistical power of content-specific constructs. However, the present research discovered a strong correlation between intrinsic and extrinsic motivation and job satisfaction, indicating a lack of discriminating validity that limits the use of HCM. Thus, this research condensed data on job satisfaction for university staff by comparing a consistent partial least square (PLSc) model to a composite model without utilizing higher-order constructs. The sample consisted of 392 individuals working in a Thai university with a total of 1,042 staff. The results show that the composite model performs better than a consistent partial least square, generating bias. Intrinsic motivation is both a direct and indirect effect on job satisfaction. Extrinsic motivation is a complementary model mediator effect. The limitation of the study is an inherent relation between intrinsic and extrinsic motivation and indicators of job satisfaction, which can cause a common factor model bias. Further studies where the partial least square structural equation model (PLS-SEM) is compared early with the covariance-based structural equation model (CB-SEM) are needed, particularly studies using composite indicators. PLS-SEM can now be used to measure both confirmatory composite analysis and confirmatory factor analysis, while CB-SEM can only estimate confirmatory factor analysis. The method of condensing data may help eliminate discriminant validity issues.

Keywords: Composite, Consistent partial least square, Condensed data, Extrinsic and intrinsic motivation, Job satisfaction, Hierarchical construction model (HCM)

Introduction

The hierarchical construction model (HCM) is a means of improving efficient models that can enhance content-specific constructs (Becker et al., 2012), and statistical power, reduce colinear formative indicators (Hair et al., 2017) and achieve parsimonious models (Polites et al., 2012). The most commonly used HCM building method consists of a reflective-reflective and reflective-formative type, including a repeated indicator (Wold, 1982) and a two-stage approach (Ringle et al., 2012). Formative use of higher-order models should be beneficial (Diamantopoulos & Winklhofer, 2001), whereas bias arises when a repeated indicator is used for higher-order models (Becker et al., 2012). Thus, appropriate common factor data with a repeated indicator approach, reflective type, and latent algorithm (PLSc). Composite models are very similar to formative models (Henseler et al., 2016), so a two-stage approach, formative type, and mode B are suitable. A reflective-formative model using a repeated indicator approach in a lower-order construct and a two-stage approach in a higher-order construct may be most fitting. However, the most likely issue with a repeated indicator approach and reflective type is the harm done to discriminative validity. Becker et al. (2012) showed alternative ways to solve this problem with an improved indicator approach and disjoint two-stage approach. The present research examines the relationship between university staff's intrinsic and extrinsic motivation and work satisfaction. Intrinsic motivation and extrinsic motivation are two step-buildings and can also be used with HCM. Many scholars use it to perform effective and advanced work on the partial least square path (Crocetta et al, 2021; Martínez Avila et al., 2021; Sarstedt et al., 2019; Schuberth et al., 2020). However, in the current study, the data on intrinsic and extrinsic motivation and job satisfaction are relevant making Becker et al. (2012) approach unable to overcome discriminatory invalidity. Structural model assumptions can often have a misleading effect if the definition lacks discriminative validity resulting from the measurement model (Farrell & Rudd, 2009). The current research’s rigorous standards explicitly lack discriminatory validity and thus prevent the use of HCM using approaches to condense work satisfaction data for university workers.

To understand motivation and satisfaction, scholars transform staff behavior and improve the efficiency and quality of the organization’s work (Machado-Taylor et al., 2011). Most research has focused on the issue of job satisfaction and dissatisfaction, which is organizational behavior researcher common issue regarding work attitude. Job satisfaction can affect various organizational activities and contribute to staff wellbeing (George & Jones, 2008). Herzberg’s two-factor theory significantly boosts exploring for advancing job satisfaction studies (Steers & Porter, 1992) that incorporate hygiene variables and motivation. Hygiene factors are represented as extrinsic components of the occupation structure that, if not met, contribute to staff' dissatisfaction. There are long discussions about how extrinsic components contribute to job satisfaction (Furnham et al., 1999). Individuals can be motivated either intrinsically or extrinsically (Hung et al., 2011). An intrinsic drive is intrinsically fascinating, while an extrinsic drive is fueled by objectives (Deci & Ryan, 1980). Extrinsic and intrinsic forms of motivation lead to different outcomes and attitudes (Ryan & Deci, 2000), positively affecting job satisfaction. It is possible that individual staff objectives and priorities are not in line with university management objectives, resulting in a conflict of goals. Universities should develop incentive programs that reinforce the connection between staff goals and motivation factors with organization objectives (Arvidsson, 2005). Many scholars (e.g., Cerasoli et al., 2014; Garbers & Konradt, 2014; Hendijani et al., 2016) find that the influence of extrinsic motivation can reduce the intrinsic motivation for job satisfaction while some scholars (e.g., Deci et al., 1999; Frey & Jegen, 2001; Kuvaas et al., 2017) find contrary results. Therefore, this work will investigate whether intrinsic and extrinsic motivation has a distinctive connection with job satisfaction. Currently, almost no studies involving higher education staff were found (Machado et al., 2011); inquiries concerning this should be performed and studied on an ongoing basis. The current research investigates the mediation effect between extrinsic motivation, intrinsic motivation, and job satisfaction on common factors (PLSc) using a latent algorithm while a composite model uses an emergent algorithm, with mode B. Additionally, Henseler (2017) explains that since all constructs are latent variables, the model is called confirmatory factor analysis (CFA). Further, when all variables are emergent, the model is called confirmatory composite analysis (CCA). This analysis aims to compare the effects of CCA and CFA, including models of mediation effect based on PLSc and composite models that do not use HCMs but rather condensed data. The results can help to increase staff satisfaction and motivation by increasing understanding, affectability, and communication concerning significant issues.

Literature review and hypothesis development

Hierarchical component model and condensed data

HCM's construction method consists of four approaches and four types. There are repeated indicators (Wold, 1982), two-stage (Ringle et al., 2012), hybrid (Wilson & Henseler, 2007), and three-stage (van Riel et al., 2017), and the type are reflective-reflective, reflective-formational, formative-reflective, and formative-formative (Ringle et al., 2012). Repeated indicators use the same indicators for both lower and higher-order constructs. The two-stage method uses first-order standard construct scores as the indicator (Henseler, et al., 2007). The hybrid approach divides the two-part indicators into lower and higher designs, each for 50% (van Riel et al., 2017). As a result, it produces confusion with an odd number of indicators. The three-stage approach is no longer viable (Cheah et al., 2019). The main shortcoming of a repeated indicator approach is that it damages the discriminative validity (Sarstedt et al., 2019), leading to inconsistent results and not considering model fit testing (van Riel et al., 2017). This shortcoming is avoided with a two-stage approach (Hair et al., 2013). However, not only the approach needed to be considered but also the type. It is necessary to find a way to use it properly in order to ensure the HCM building system incorporates a type-approach combination.

Fornell and Bookstein (1982) note that a set of measurable effects in a two-stage framework that describes a reflective model is, therefore, suitable for a repeated indicator approach. Although a set of latent variables builds a formative model (Burt, 1976) while evaluating stage one scores (Wilson & Henseler, 2007), that may complicate interpretation. The use of formative in higher-order models would be beneficial (Diamantopoulos & Winklhofer, 2001), but using a repeated indicator approach in the second stage is unacceptable and may cause bias (Becker et al., 2012; Hair et al., 2017). Additional~~,~~ uses for HCM include the reflective-reflective and reflective-formative type (Cheah et al., 2019). Thus, the repeated approach of the indicator is appropriate for the reflective model in the first-order construct.

However, it will be detrimental to the discriminant validity. Sarstedt et al. (2019) overcame this problem by manually calculating the discriminative validity~~,~~ but be still lacked information on model fit. In the absence of discriminative validity, the constructs influence the variance of more than just the observed variables to which they are theoretically related. The results cannot confirm whether the proposed structural paths are absolute or arose from statistical inconsistencies (Farrell, 2010). The best way to solve this problem is through an improved indicator approach and a disjointed two-stage approach (Becker et al., 2012). They calculated the improved repeat indicator approach without creating a higher-order construct. It still generated standard construct scores that became higher-order indicators for a disjointed two-stage approach. Not surprisingly, Hair et al. (2017) argued that a disjointed two-stage approach might be reflective or formative in both the first and second stages. Nonetheless, current research data on intrinsic and extrinsic motivation and job satisfaction are still relevant, even though Becker et al. (2012) approach still harms to the discrimination validity. The current research thus puts aside a higher-order model and uses the condensation data method described in the data analysis section.

The PLSc and composite model

PLS-SEM consists of measurement and structural models. A measurement model defines the relationship between constructs and indicators, while a structural model examines variables' relationship. Measurement models consist of reflective, causal-formative, or composite, depending on the nature of the design. Behavioral science models typically use latent variables, mainly focused on reflective assumptions where a common factor involves a new manifestation of minus variable measurement errors (Kock, 2015). This is the primary source of the estimated mode a bias parameter (Antonakis, et al., 2010) and abandonment (e.g., Rönkkö et al., 2015). Dijkstra and Henseler (2015a, 2015b) suggest the use of PLSc to solve this mode a issue. However, PLSc may not be perfect as it uses a bias-corrected parameter generally producing statistical power lower than other methods (Kock, 2017). In cases where the indicators are an antecedent for using the construct's causal-formative measurements using the mode B algorithm, it, like for multiple regressions, creates measurement errors in the constructed variables. Multicollinear indicator relationships do not occur if any indicators are omitted, resulting in increased measurement error. All indicators have one definition (Bainter & Bollen, 2015), each left to confounding interpretations that can change the constructed meaning (Henseler et al., 2015). Many scholars have found such a casual-formational deficiency as bias (e.g., Rönkkö et al., 2016) and of no use at all (Rigdon, 2016).

Causal-formatives prohibit use due to misinterpretation (e.g., Benitez et al., 2020), and many scholars (e.g., Aguirre-Urreta et al., 2016) consider casual formatives to be misleading if R^2 is less than one. The current research uses a composite model that assumes all constructs are artifacts or design constructs. The design constructs describe their composites as indicator mixtures (Henseler, 2017), and composites are weighted as linear indicator combinations (Kock, 2017), thus ensuring that the composites have no error terms (Schuberth et al., 2018). Composite measurements have few overall drawbacks associated with inter-constructed correlations and related indicator loads between indicators (Henseler, 2017). They do not require any assumptions about the relationship between the value any of its measurements that would be unqualified. Composite model parameters include nomological networks, multicollinearity, weight significance, factor loading, and weight relevance (Henseler, 2017). Hair et al. (2020) suggested the same thing as Henseler (2017), also stating they incorporated convergent validity (redundancy) and assessed predictive validity.

Confirm composite analysis and confirm factor analysis

There are two distinct concepts of CCA: Hair et al. (2020) and Henseler et al. (2014). Hair et al. (2020) suggested a new measure under the same name as the CCA. Their CCA (2019) validated and showed the reliability of the PLS-SEM measurement model. Therefore, Hair et al. (2020) CCA may include all kinds of models: classical reflective, causal-formative, common factor (PLSc), and composite, while Henseler et al. (2014) focus only on emergent variables. Traditional PLS-SEM, reflective, and causal-formative models all have their issues. The reflecting measurement approach is based on a composite variable and has no error term on either the indicator or the construct. PLS-SEM will likely produce bias and misestimates when data is modeled as a common factor (Aguirre-Urreta & Mikko Rönkkö, 2017; Dijkstra, 1983). Thus, PLSc was born to solve this problem (Dijkstra & Henseler, 2015a, 2015b) by having common factors determine the indicators (Schuberth et al., 2018). In causal-formative models, scholars (e.g., Aguirre-Urreta et al., 2016) find it difficult to remove a single causal-formative predictor. All indicators in a single construct use a single definition (Bainter & Bollen, 2015), each one leading to confounding interpretations. Henseler (2017) proposed to use MIMIC to solve this problem. Therefore, the Hair CCA et al. can be both reflective and formative, while the Henseler CCA uses only a composite or emergent variable that is formative.

When all of the constructs in the model are unmeasured latent variables, that PLS-SEM would refer to as CFA, they are calculated using PLSc. The PLS-SEM will call on CCA when all the constructs are emergent variables. In the context of CCA, indicators are used to measure a linear combination of composite or emergent variables (Schuberth, 2020). CFA will serve as a reflective variable for latent variables and a formative variable for emergent variables in SEM (CCA). Henseler's group provides a CCA that shares model specifications, model identification, and model estimations with the CFA (Schuberth, 2020). However, CFA regularly considers latent variables, while CCA observes the composite inter-relationships of all variables. CCA is based on a composite indicator that is created with artifact construct (Henseler, 2017) and is viewed as a simple object that uses path diagrams to explain its relationship. This makes CCA applicable to disciplines exploring theoretical principles and interactions with theoretical concepts of behavioral science. Furthermore, composite, emergent, or artifact variables may be constructed based on Henseler's (2017) findings used much less often than latent variables due to the lack of statistical methods to test them (Henseler & Schuberth, 2020). Hair et al., (2020) findings may lead to misconceptions about CCA. They refer only to the name but use it differently without criticizing the original CCA. As a result, this study is based on Henseler et al., (2014)'s CCA.

Rajabhat universities in Thailand

Previously, Rajabhat Universities were called Rajabhat Institutes and were initially established as teachers' college programs. In 1995, they were formally raised to university status. There are now 38 Rajabhat universities located all over the country. It is usually more accessible for the student to be admitted there than at other government or public universities. Several Rajabhat universities offer graduate degrees, some up to the doctoral level.

Satisfaction and motivation

Job satisfaction refers to positive feelings and emotional attitudes towards work (Oshagbemi, 1999), including one's position and function (Robbins et al., 2009), which have an overall positive impact on one's employment (Feldman, 1985). This involves organizational success and employee efficiency, and combining positive work emotions. Spector (1997) measured it using nine elements: wage and benefits, job promotion, management, fringe benefits, contingent rewards, working conditions, staff, type of job, and communication. For higher education, personnel is a valuable resource, working rigorously to achieve their goals. They provide students with learning and accomplishments~~,~~ while urgently needing support and satisfaction for the efficiency of higher education foundations (Machado et al., 2011). Job satisfaction may reflect work behaviors such as citizenship, absenteeism, and turnover; ideally, universities should increase staff satisfaction and inspire a smooth reduction in absenteeism (Gazioglu & Tansel, 2006). An organization's level of staff satisfaction, whether positive or negative, has a significant effect on its efficiency and productivity. Some scholars found that the work atmosphere and staff motivation can affect job satisfaction.

Motivated and committed employees usually perform better and enjoy their work more than non-motivated workers. The various motivational theories include a framework where the organization may adopt specific approaches to encourage and boost the satisfaction level of workers to ensure high morale, better efficiency, and productivity. Accordingly, universities should be mindful of developments in the business environment and update staff facilities annually to ensure they can perform their duties with maximum energy and satisfaction. Specific institutional issues, conditions, and situations that affect academics' working lives can determine motivation. Personal motivation begins with the mental affirmation that pain is absent at the moment of the person's experience, accompanied by a psychological desire to do something, followed by motivational physical activity. Motivation, therefore, it closes the satisfaction-performance loop and has to do with a collection of interrelated factors that explain a person's actions, and maintain regulated or affected variables and unique abilities, skills, and knowledge (Campbell & Pritchard, 1976). The theory of two-factor motivation of Herzberg et al. (1959) indicated that satisfaction and dissatisfaction were not two opposite limits of a similar scale, but rather, two separate components created by different parts of the job, namely hygiene factors, or extrinsic, and motivators, or intrinsic.

Intrinsic motivation for the effects of extrinsic rewards

Motivation research has differentiated between intrinsic and extrinsic motivation for many years, with literature for each motive. Some are writing about management believes extrinsic rewards decrease intrinsic motivation (e.g., Cerasoli et al., 2014; Jovanovic & Matejevic, 2014). Monetary incentives are a major negative influence on intrinsic motivation and can have significant long-term negative impacts when organizations seek to control individual activities (Deci et al., 1999). Eisenberger et al. (1999) strongly disagreed with Deci et al. (1999) findings and recommendations, and more appropriate research is needed. McCullagh (2005) provides a framework for other research fields with five theories, explains possible mechanisms, and proposes several strategies. The first, Cognitive Evaluation Theory (CET: Deci & Ryan, 1985), eliminates intrinsic motivation through extrinsic rewards. The second, Overjustification Effect, implies a reduction of extrinsic rewards through intrinsic motivation (Lepper et al., 1973). The third and fourth, Self-Determination Theory (Gagné & Deci, 2005) and the Theory of General Interest (Eisenberger et al. 1999), can improve intrinsic motivation, under some circumstances, by use of extrinsic rewards. The fifth, Motivation Crowding Theory (Frey & Jegan, 2001), stipulate that intrinsic motivation can be overwhelmed by extrinsic motivation rewards. Theories are essential for trying to explain why and under what conditions predictable effects arise. Hendijani et al. (2016) note that Deci et al. (1999) have the best analysis and that the findings confirm the critical predictions of CET on the impact of contingent motivation incentives. Therefore, this study will analyze the relationship between intrinsic and extrinsic motivation using a hypothesis constructed with Deci et al.'s theory (1999).

H1: Intrinsic motivation is positively related to extrinsic motivation.

Extrinsic motivation & satisfaction

Extrinsic motivation refers to the job characteristics of the tasks themselves, including rewards or compensation, such as salaries, work security, and adequate resources (Herzberg, 1959). It refers to operation performance to achieve some distinct outcomes (Ryan & Deci, 2000). When extrinsically driven, people pursue incentives such as money and prestige or journal publication (Makki & Abid, 2017). Extrinsic motivation provides jobs with external factors such as benefits, constructive feedback, and the worker's desire to meet social expectations (Jessen, 2010) instead of doing the job itself. The essential distinction between it and intrinsic motivation is that the latter refers to doing something because it is inherently exciting or pleasant, while the former refers to doing something because it leads to a particular goal (Deci & Ryan, 1985). Self-determination theory (SDT; Deci & Ryan, 2008) suggests that individuals can be involved in an action for various reasons or motives~~,~~ and identify as more or less self-determined (autonomous).

Deci and Ryan (1985) suggested six modes of regulation across a continuum of self-determination, with behaviors ranging from high autonomy (intrinsic motivation) to medium (extrinsic motivation) and low autonomy (low motivation). The six behavioral regulations are motivation, external regulation, introjected regulation, identified regulation, integrated regulation, and intrinsic regulation. Extrinsic motivation is thus external regulation, introjected regulation, identified regulation, and integrated regulation. External regulation refers to behavior conducted to satisfy market demand or an externally determined contingency of compensation. It is the most minor autonomous type of extrinsic motivation, including the classic case of inspiration to get rewards or avoid punishment (Zamarripa et al., 2018). Introjection defines a kind of internal regulation that is often very controlling because people conduct these acts with the feeling of pressure to escape shame or anxiety or gain ego-enhancing rewards or pride. When workers participate in behavior due to various constraints that can increase tension and stress (Kastrinos, 2001). Identified regulation involves the granting of perceived value to practice so, it action is accepted when it is of personal importance (Ryan & Deci, 2000). It happens when workers engage in an activity because it is viewed as high-value and essential to them, even though they do not enjoy the action itself. Integrated regulation occurs through self-examination and the alignment of new rules with other values and needs. This form of extrinsic motivation is the most autonomous (Ryan & Deci, 2000). Integrated regulation includes motivation, the most self-determined way of extrinsic motivation. This study uses extrinsic motivation for university workers to be wages and benefits, interpersonal relationships, working conditions, and university policies. Herzberg (1959) essentially indicates that extrinsic motivation is positively related to job satisfaction, so that the study will hypothesize the following.

H2: Extrinsic motivation is positively related to job satisfaction.

Intrinsic motivation and satisfaction

Intrinsic motivation is the commitment to one’s wellbeing, happiness, and accomplishment in one’s acts (Deci, 1972), which contribute to one’s satisfaction and fulfillment of doing so. Intrinsic motivation emerges when acting occurs for its purpose rather than for receiving material or social reinforcement. People who are intrinsically motivated voluntarily engage in an activity without external or internal cohesion and expectant rewards (Teye et al., 2019). It is the most self-determined or autonomous form of motivation where the underlying actions are performed purely for the pleasure of the act itself. Intrinsic motivation (IM) can be divided into three forms: (1) knowledge, (2) accomplishment, and (3) stimulation (Vallerand et al., 1992). Intrinsic knowledge motivation is an activity undertaken for the pleasure and satisfaction derived from learning, exploring, or trying to understand something (Vallerand, 2001). Intrinsic accomplish refers to engaging in activities for the enjoyment and satisfaction felt while attempting to accomplish or produce (Fortier et al., 1995). Intrinsic motivation to experience stimulation occurs when someone gets involved in an activity to feel pleasure from engaging in that activity (Fortier et al., 1995). In addition to enhancing performance, intrinsic motivation can influence various habits, triggers, emotions, and attitudes that are necessary rewards to impact experiences (Lemyre et al., 2006). Intrinsic motivation correlates with positive effects, feelings, and beliefs that may protect workers from stressors and negative emotions (e.g., Deci & Ryan, 2008). Nonetheless, the intrinsic motivation observed by Gagné et al. (2010) can be both positive and negative in terms of optimism, job satisfaction, affective and normative organizational involvement, self-reported psychological health and wellbeing, as well as deliberate psychological distress and turnover. This study constructs the hypothesis as follows;

H3: Intrinsic motivation is positively related to job satisfaction.

The effect of the extrinsic motivation mediator

Mediation is a research design in which a third variable, a mediator variable, interferes between two related constructs (Sarstedt et al., 2020). Researchers examine whether a change in the independent construct results in a difference in the mediator variable, which influences the dependent construct of the model (e.g., Demming et al., 2017). PLS-SEM lacks study mediation work (Hair et al., 2017), where researchers have only focused on direct relationships. High-capacity applications are available for simple analysis of mediation effects. Nitzl et al. (2016) suggested two steps to summarize the essential mediator effect. Step 1: Determining the significance and magnitude of the indirect effects. To determine the mediation effect, the indirect effects AxB (Figure 1) in Step 1 must be significant, the volume of which is the product of their path coefficient. Step 2: Determining the type of mediation. A mediating effect always occurs when the indirect effect is of significance in Step 1. Current mediation literature addresses two forms of mediation, full and partial mediation. The full mediator effect occurs when C (Figure 1) is insignificant. This means only an indirect effect through the mediator (Cepeda et al., 2017). The magnitude of the indirect effect (mediation effect) is the product of AxB. The total result is an indirect effect plus C. Partial mediation comprise complementary and competitive effect. In a complementary partial mediation, the direct and indirect effects point in the same direction and are significant, while A×B×C is positive. This suggests that a portion of the EM mediate affects the JS while the IM still explains a part of the JS independent of the EM. The complementary mediation hypothesis indicates that the intermediate variable can clarify, confuse, or falsify the relationship between independent and dependent variables. In a competitive partial mediation~~,~~ or negative confounding, the direct effect C and indirect effects AxB point differently. A negative rating indicates the role of fair mediation in Step 2. It suggests that the EM mediates a portion of the IM's effect on the JS, while the IM still explains a part of the JS independent of the EM. If the indirect impact is insignificant in a narrow sense, then mediation cases cannot be considered. There will only be a direct effect if the mediator variable has no impact and if the indirect effect A×B is not significant. This indicates that there is a direct, non-meditating effect. There is no effect if neither the indirect effect nor the direct effect is significant, but the total impact can still be substantial. Competitive mediation shows that inconsistent models consider complementary partial mediation (Cepeda et al., 2017). They propose that the variance accounted value (VAF) be the criterion for measuring the strength or portion in the case of partial mediation [AxB/(AxB)+C] if the full mediator effect is higher than 80%. In comparison, the partial mediator effect is lower.

The current study examines the mediating role of extrinsic motivation between intrinsic motivation and job satisfaction. Intrinsic motivation relates to the inherent features of work and characteristics associated with the job itself, such as the ability to give workers a sense of accomplishment, purpose, obligation, or accomplishment (Kalleberg, 1977). It has important implications for the overall satisfaction of social workers at work and the desire to commit to their job (Guay et al., 2010; Huxley et al., 2005). Thus, the intrinsic motivation component also acts as the most significant motivating factor for social workers who connect with clients through support and assistance, seeking to transform and improve clients' lives (Jessen, 2010). It is a kind of vital motivation, and early childhood experiences do not exclusively drive behavior. While external pressures and responsibilities gradually diminish the capacity to be emotionally inspired, it forces individuals to take responsibility for non-intrinsically significant tasks. In colleges, for example, intrinsic motivation weakens with each grade (Ryan & Deci, 2000). As in the literature, the current study focuses on the mediating role of extrinsic motivation, hypothesizing as follows.

H4: Extrinsic motivation (mediator) significantly mediates the relationship between intrinsic motivation (independent variable) and job satisfaction (dependent variable).

The conceptual frameworks

The current study aims to compare PLSc and the composite model as applied to extrinsic and intrinsic motivation affecting job satisfaction of university staff, where all variables assume a common factor and artifact. This study does not recognize discriminatory invalidity at any stage, thus avoiding using HCM, since all latent variables are somewhat relevant. As a result, the current research uses a single order construct to bring all the member indicators into each construct and condensation indicators into five and four for intrinsic and extrinsic motivation, respectively. The intrinsic construct indicator includes the indicator of achievement, recognition, self-employment, responsibility, and advancement. The extrinsic construct indicator comprises an indicator of wages and benefits, interpersonal relationships, working conditions and, university policies. Fig.1 indicates the conceptual structure that PLSc creates in the sphere, while the hexagon-composite model hypothesizes that both models are the same. Each construct variable represents a latent variable capable of being utilized in CFA. On the other hand, the CCA model will use the same questionnaire to generate an emergent latent variable (Hubona et al., 2021).

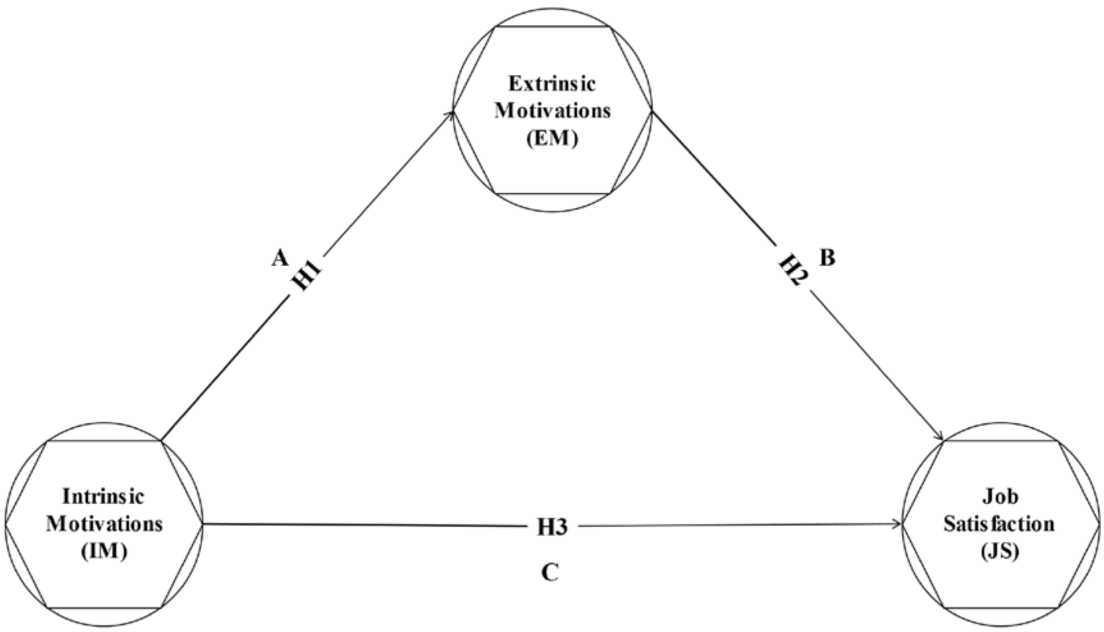

Figure1 Conceptual framework

Methodology

Sample and population

This is a case study of Valaya Alongkorn Rajabhat University, which has a population of about 1,042 workers, 534 of whom are professors and 508 of whom are non-faculty (October 2019). Non-probability sampling was used in this study, a convenient form of sampling for university staff as they can then answer the questionnaires. Convenience sampling is a technique used for selecting university staff who are often encountered and easily accessible. The sample size was determined using the Soper (2021) website and was calculated using five indicators: effect size (0.18), statistical power (0.80), number of latent (3), number of observations (13), and probability level (0.05). It generated a minimal sample size of 371 individuals, following which this study collected 392 to meet that minimum sample size requirement.

Questionnaires and measurement

The questionnaire consists of three primary groups of questions: intrinsic and extrinsic motivation and job satisfaction. Intrinsic motivation consisted of five constructs: achievement (IM1), recognition (IM2), work-itself (IM3), responsibility (IM4), and advancement (IM5). Extrinsic motivation consisted of wages and benefits (EM1), inter personnel relationships (EM2), working conditions (EM3), and university policies (EM4). Job satisfaction consisted of four constructs: labor wages, relationships, work, and equipment indicators. The questionnaire was developed using Raso's finding (2012); some indicators were dropped to more efficiently calculate the number indicators. The selection indicator criterion is the best loading factor of magnitude and weight significance for each intrinsic and extrinsic motivation component in the initial calculation of the actual scenario model. When the original intrinsic motivation indication was decreased from twenty-three to five, the loading factor increased from 0.716 to 0.770, but the weight indicators remained significant except for the advancement indicator. The initial extrinsic motivation indicator consisted of twelve indicators which were then reduced to four with a loading factor of 0.728 to 0.790. The weight of all the indicators was significant. All of the indicators for intrinsic and extrinsic motivation and job satisfaction are new measurements in PLSc and are composite as in the result. As displayed in the appendix, the initial questionnaire collected the data in the Thai language. The survey consisted of 45 questions divided in to two parts. The first section considered of a 6-question bibliography, while the second section included 39 items on intrinsic motivation (23), extrinsic motivation (12), and job satisfaction (4). The answer were given using the Likert 5-point scale, ranging from "strongly accept" to "strongly disagree."

Data analysis

Usually, Partial Least Square Structural Equation Model (PLS-SEM) consists of two primary models, the measurement and the structural model. In addition, the saturation and estimation model fit the model goodness test (Henseler, 2017). The approach used bootstrapping to assess the discrepancy between the results and the matrix of model-inferred correlation. The model fit parameters are the standardized root mean square residual (SRMS), the unweighted minimum square discrepancy (d_{ULS}), and the geodesic discrepancy (d_G). First, two conditions must be considered: the effects of the 95 percent (HI95) quantile bootstrapping and then the 99 percent (HI99) that will perform below the requirements. Second, if the first condition is unlikely, the SRMR must be below 0.08 (Hu & Bentler, 1999). If these two conditions are not met then the model is meaningless.

The contains different criteria for considering its quality between the common factor or reflective model, the causal-formative model, and the composite model. PLSc, or latent algorithm, measures reflective criteria such as internal consistency reliability, indicator reliability, convergent validity, and discriminative validity. For the internal consistency and test accuracy, the questionnaire will calculate the same parameters as Dijkstra-Henseler's rho and Jöreskog's rho, and Cronbach's alpha above 0.70. An indicator reliability with the factor loading would exceed 0.708 (Henseler et al., 2015) indicates that the indicator can determine its construct. It may explain more than 50% of the indicator variance, making the item quite reliable. A convergent validity test with the Average Extracted Variance (AVE) exceeding 0.50 in the construct score indicates an indicator variance (Hair et al., 2017). The Hetrotrait-Monotrait Correlations (HTMT) discriminating validity check should be distinct, below 0.85 (Henseler et al., 2015).

The parameters for the composite measurement can be the same as for the formative ones (Hair et al., 2020). Nomological network, multicollinearity, weight significance, and loading factor are all relevant (Henseler, 2017). A nomological net means that the size and the sign are large enough, positive and theoretically based, and refer to the constructions defined as composites, usually requiring an embedded context. (Henseler, 2017). Multicollinearity measures with a VIF of less than five (Hair et al., 2011). The weight would be significant if the negligible load reaches 0.5.

The structural model parameters should consider the path coefficient size and sign, including the effect size (f^2), the relationship size (R^2), and the predictability size (Q^2). The path coefficient should reach 0.20, and the significance and sign should be positive. The effect size should be more than moderate, or 0.15 (Cohen, 1992), and R^2 should be more than average, or 0.33 (Chin, 1998).

The condensed method includes two calculations in which the first measure is to put all of the indicator members into each construct. Intrinsic motivation consists of twenty-three indicators of achievement (5 indicators), recognition (4 indicators), work itself (5 indicators), responsibility (5 indicators), and advancement (4 indicators). Extrinsic motivation consists of twelve indicators of wages and benefits, interpersonal relationships, working conditions, and university policies, each comprised of three indicators. Job satisfaction comprises of four indicators-the first is calculated using PLSc with algorithm latent while composite model using algorithm latent and mode B. The selected indicator criteria are magnitude factor loading and weight significance for the best indicator of each intrinsic and extrinsic motivation component. The current study data show that all indicators of job satisfaction are well defined. Thus, the intrinsic and extrinsic motivation data were condensed to five and four indicators, respectively, keeping all of their characteristics (and information) since all aspects were include. The second measurement uses the same scenario as for the first calculation. The condensed data method may be appropriate with a composite model for dimension reduction, reflecting a concept's salient features adequately (Dijkstra & Henseler, 2011).

Results

The demographic data

Table 1 shows the demographic data: 47.60% of the participant were women aged between 41-50 or more than 50 years, with a distribution of 38.50% and 28.60%, respectively. For education, 45.70% held a bachelor's degree and 45.40% held a master's degree. The data shows that about 45.40% and 54.60% are faculty members and non-faculty members, respectively, 69.20% are married and their monthly income is 30,001-40,000 baht or more than 40,000 baht, 24.50% and 39.80%, respectively.

Table 1 The demographic data

Variable		**Frequency**	**Percent**
Sex	Female	186	47.60
	Male	206	52.60
Age	20-30 years	20	5.10
	31-40 years	109	20.80
	41-50 years	151	38.50

Variable		Frequency	Percent
	More than 50	112	28.60
Education	Primary	10	2.60
	Secondary	15	3.80
	Diploma	10	2.60
	Bachelor	179	45.70
	Master and higher	178	45.40
Occupation	Faculty	178	45.40
	Non-faculty	214	54.60
Status	Single	81	20.70
	Married	272	69.40
	Separated	25	6.40
	Divorced	14	3.60
Income	5,000-10,000 baht	12	3.10
	10,001-20,000 baht	36	9.20
	20,001-30,000 baht	92	23.50
	30,001-40,000 baht	96	24.50
	More than 40,00 baht	156	39.80

Overall model fit

Table 2 shows the overall model fit; all PLSc model parameters are higher than the composite model and 99% are higher than the bootstrap quantile, but SRMR is lower than 0.08 for the same composite model.

Table 2 Overall model fit

		Saturated model			Estimated model		
Models	**Parameters**	**Value**	**HI95**	**HI99**	**Value**	**HI95**	**HI99**
PLSc	SRMR	0.063	0.039	0.042	0.063	0.039	0.042
	d_{ULS}	0.361	0.139	0.160	0.361	0.139	0.160
	d_G	0.144	0.052	0.058	0.144	0.052	0.058
Composite	SRMR	0.058	0.032	0.036	0.058	0.032	0.036
	d_{ULS}	0.309	0.096	0.115	0.309	0.096	0.115
	d_G	0.126	0.037	0.042	0.126	0.037	0.042

Measurement model

For the PLSc, the reflective quality parameters are internal consistency reliability, reliability of indicators, convergent validity, and discriminative validity. The internal consistency reliability is Dijkstra-Henseler’s rho, Jöreskog’s rho, and Cronbach’s alpha between 0.630 and 0.672 as shown in table 3. The indicator reliability has a factor loading higher than 0.708, and all indicator factor loadings are below the requirements. The convergent validity has an average variance extracted (AVE) above 0.5, with the value being between 0.289 and 0.301 as shown in Table 3. Table 5, reveal that HTMT recognizes the discriminating validity as 0.996 to 1.07. The results show that all of the parameters to lower than the standard.

Table 4 shows the composite model consistency, representing the nomological network, multicollinearity, weight significance, and loading factor. Concerning the nomological net, all indicators have positive signs as based on the theories. For the multicollinearity, all VIF indicators are below 5, between 1.111 (JS1) and 1.306 (RESP). the weight significance shows that all of the value intrinsic motivation, extrinsic motivation and job satisfaction are significant and tagged with an asterisk. The composite indicator parameters were well constructed for the measurement model.

Table 3 Internal consistency reliability

Construct	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_c)	Cronbach's alpha(α)	The average variance extracted (AVE)
Intrinsic Motivation	0.672	0.670	0.669	0.289
Extrinsic Motivation	0.634	0.631	0.630	0.301
Job Satisfaction	0.618	0.617	0.618	0.288

Table 4 Questionnaire

Indicators	Factor loading (PLSc)	Weight	Factor loading	VIF
		Composite		
Intrinsic motivation				
IM1: I am proud to makes this university a success.	0.519	0.356*	0.638	1.157
IM2: I can solve my coworkers' problem.	0.499	0.256*	0.588	1.186
IM3: My job is challenging.	0.571	0.384*	0.708	1.257
IM4: I am getting my job done efficiently.	0.517	0.194*	0.624	1.306
IM5: My work can be more stimulating than other positions.	0.579	0.329*	0.696	1.301
Hygiene (Extrinsic) motivation				
EM1: My compensation suits my success and workload.	0.575	0.447*	0.750	1.211
EM2: My colleagues accept and praise me.	0.488	0.275*	0.585	1.147
EM3: My job suits my skills and experience.	0.548	0.335*	0.682	1.238

Indicators	Factor loading (PLSc)	Weight	Factor loading	VIF
		Composite		
EM4: My university is a great environment and a healthy workplace.	0.577	0.382*	0.720	1.251
Job Satisfaction				
JS1: I appreciate my salary.	0.540	0.480*	0.709	1.111
JS2: My colleagues can always help mee solve problem when I have job issues.	0.505	0.259*	0.614	1.242
JS3: I am delighted with my job.	0.563	0.395*	0.703	1.239
JS4: I am satisfied with the office equipment and supply.	0.535	0.330*	0.677	1.237

* t-statistics > 1.96 (Kock, 2016)

Table 5 The Hetrotrait-Monotrait correlations

Construct	Intrinsic motivation	Extrinsic motivation	Job satisfaction
Intrinsic motivation			
Extrinsic motivation	0.996		
Job satisfaction	1.006	1.073	

Structural model

PLSc has one significant direction: intrinsic motivation to extrinsic motivation and a magnitude of 0.994 and size effect of 89.026. The R^2 has an extrinsic motivation of 98.90%. The other two directions are insignificant, with has an inherent negative motivation value as shown in Table 6 and Fgiure 2. The composite model defines all directions very well, as shown in Table 6 and Figure 3. The results show that the path coefficients of the PLSc are biased.

Table 6 Structural model result

Model	Hypothesis	Direct effect	p-value	f^2	% Bootstrap confidential interval		Decision
					2.5%	97.5%	
PLSc	H1: IM -> EM	0.994	0.000	89.026	0.914	1.084	Support
	H2: EM -> JS	6.407	0.911	-0.974	-17.279	26.805	Not Support
	H3: IM -> JS	-5.365	0.894	-0.683	-26.164	18.257	Not Support
Composite	H1: IM -> EM	0.653	0.000	0.741	0.592	0.717	Support
	H2: EM -> JS	0.434	0.000	0.234	0.322	0.558	Support
	H3: IM -> JS	0.371	0.000	0.170	0.260	0.474	Support

Figure 2 The confirmatory factor analysis (CFA)

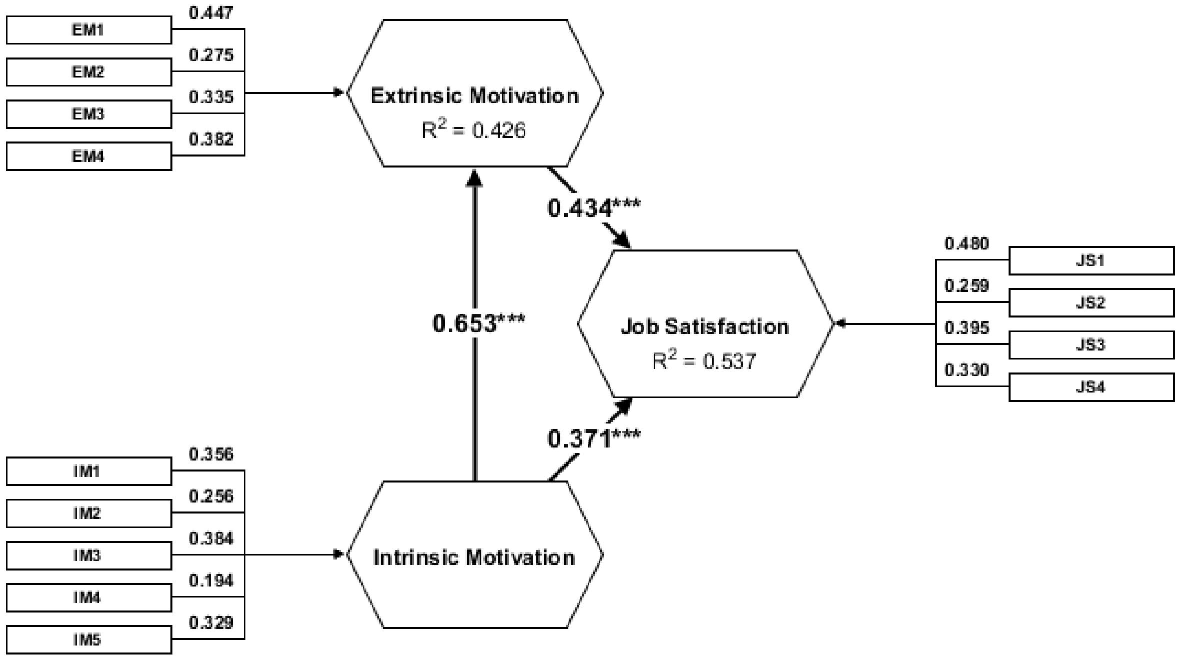

Figure 3 The confirmatory composite analysis (CCA)

Mediator effect

Table 7 shows that the indirect mediating role effect in the PLSc model reveal that AxB is an insignificant mediator effect. In the composite model, since AxB and C are significant, the mediator effect type is complementary partial mediation, and the magnitude is 0.289 (from 0.653x0.434). The VAF is 0.433 from [0.653x0.434/ (0.653x0.434) +0.371], or 43.30%, which is below 80% (Cepeda et al., 2017). Thus, it is a complimentary mediation effect.

Table7 Mediator effect

Model	Hypothesis	Indirect effect	p-value	% Bootstrap confidential interval		Decision
				2.5%	97.5%	
PLSc	H4: IM -> JS	6.371	0.894	-17.312	26.739	Not support
Composite	H4: IM -> JS	0.289	0.000	0.204	0.381	Support

Discussion

Summary of research

The present study avoided any problems of discriminatory validity at any stage of the research. Discriminant validity ensures that a constructed test is empirically unique, identifying interesting phenomena not found in a structural equation model (Hair et al., 2010). The researchers use a lower-order model and a repeated indicator approach that is counterproductive to discriminatory validity. The usual way to solve this problem is to improve the repeated indicator approach (Becker et al., 2012). But this approach is still detrimental to the current study data's discriminatory validity after it is used. Therefore, the present study used single-order condensation data. The first number was set at twenty-three for intrinsic motivation, at twelve for extrinsic motivation and at four for job satisfaction to measure the PLSc and composite model using algorithm latent and emergent with mode B, respectively. For each intrinsic and extrinsic motivation element, the best indicator was selected using factor loading magnitude and weight significance. All indicators of job satisfaction were appropriate in the context of the selected criteria.

The main objective was to examine the mediator effect of extrinsic motivation on intrinsic motivation and job satisfaction by comparing PLSc and the composite model. The impact of the extrinsic motivation mediation was a partial, complimentary mediation effect in the composite model, while the PLSc generated bias. In line with Sarstedt et al. (2020), a composite-based structural equation model (SEM) was a superior approach to factor-based SEM when estimating complex mediation models. PLSc's path coefficient bias may confirm Farrell (2010), who states that the lack of discriminating validity may not confirm whether the proposed structural paths are real or arise from statistical inconsistencies.

Interpretation of the finding

The current study did not use a hierarchical component model, but condenses twenty-three and twelve intrinsic and extrinsic motivation indicators to five and four indicators, respectively to prevent damage to the validity of discrimination at any HCM point. As a result, the composite model was much better than the PLSc model. Per Dijkstra and Henseler (2011), composite models were identified as a method for condensing data that reduce the dimensions to represent the system's main features. It is a useful tool to construct new entities capturing structures, compounds, and other components (Rigdon, 2014), thus relaxing the strong assumption that a common factor explains all covariation within an indicator block. The composite model does not restrict covariances between the same indicators (Henseler et al., 2016). Thus, linear combinations of predefined or estimated weights distinguish the composite model from its indicators (Henseler et al., 2014). It offers a more general and potentially realistic approach to measurement, especially when considering formative measurements (Rigdon, 2014). Common factor proxies cannot be assumed to have more considerable significance concerning the existence or nature of conceptual variables than composite proxies do (Rigdon et al., 2017). In the case of all constructs, the link relates to the fact that the composite condensed data model may be better suited than the PLSc or HCM. As stated by van Riel et al. (2017) producing a repeated indicator approach or two-stage approach to HCM may produce two drawbacks. First, they might produce inconsistent estimates. Second, they might not include model fit tests and, therefore, not provide empirical evidence for or against a hierarchical construct.

In terms of data, the intrinsic motivation, both the direct and partial complementary mediating effects was thought to be an extrinsic motivation for job satisfaction. The mediator between them is, therefore, the extrinsic motivation. The latter indicator would directly affect work satisfaction in line with Gagné et al. (2010). The answers to the following statement demonstrated that: "I am proud to makes this university a success". "I can solve my coworkers' problem". "My job is challenging". "I am getting my job done efficiently". and "My work can be more stimulating than other positions". There were other university indicators besides these such as appropriate compensation for workload, good colleagues, puts the right person in the right work position, a pleasant environment and a lively area of work all of which can act as mediators to influence the intrinsic motivation for the job satisfaction of university staff.

Theoretical implications

The results indicate that the central aspects of intrinsic motivation concern achievements, regulations, self-work, responsibility, and advancement. In addition, for university staff, wages and benefits, interpersonal relationships, working conditions, and university policies are well-organized extrinsic motivation factors-the present study's two central theories of self-determination (SDT) and Herzberg's two-factor theories. SDT explains the intrinsic motivation and extrinsic motivation factors promoting personality growth and behavioral self-regulation to improve people's wellbeing and success in organizations and society. Herzberg's theory emphasizes employee motivation, depending on the work itself (intrinsic motivation), and the working environment (hygiene or extrinsic motivation). The results suggest that intrinsic and extrinsic motivation affect job satisfaction, and that extrinsic motivation is also a complementary mediator between intrinsic motivation and job satisfaction. This research supports the two theories state that both intrinsic and extrinsic motivation affect job satisfaction, leading to increased productivity at the university. SDT and Herzberg's two-factor theories could be useful in providing an essential theoretical framework for understanding and promoting the motivation and satisfaction of workers and designing best practices to enhance their university's actions and results. The results show a positive relationship between intrinsic and extrinsic motivation in line with Deci et al. (1999) and Hendijani et al. (2016).

Concerning methodology theory, the results confirm that the composite model is ideally suited to the common factor model, particularly for the intrinsic and extrinsic motivation and job satisfaction of university staff. They use condensation data primarily to reduce dimension. It is key reason why the composite model does not impose any restrictions on the association between single artifact indicators (Henseler et al., 2014), leading to indicators that do not necessarily display a particular correlation pattern. This study confirms that the composite model in this scenario is better suited than the common factor model or PLSc.

Practical implications

Staff dissatisfaction can lead to university inefficiency and cost increases, harming a university's reputation. Research in this area, which helps universities retain their key staff, can in particular help increase job satisfaction, and is therefore essential. The causal process in which intrinsic and extrinsic motivation keeps workplace satisfaction must be understood. Universities should balance the benefits and motivation and satisfaction activities they offer to match the staff's needs. The universities should become aware of what intrinsic and extrinsic factors relate to their university's success and apply them to other levels of their organization. Intrinsic motivation factors directly impact job satisfaction and indirectly, the influence of the extrinsic motivation mediator. University efficiency can improve with job satisfaction, which includes intrinsic and extrinsic motivation. Universities can consider developing themselves based on job satisfaction, and intrinsic, and extrinsic motivation.

In the context of methodology, PLS-SEM may have been developed at an early stage than the covariance-based structural equation model. However, they were developed in the same era, CCA, one of the two main modes discussed around 2014 (e.g., Henseler et al., 2014; Rönkkö & Everman, 2013) as was PLSc (Dijkstra & Henseler, 2015a, 2015b) or common factor in 2015. While Schuberth et al. (2018) note that the composite model is an old school concept in multivariate data analysis (Pearson, 1901), it has been recently applied to a partial least square (Henseler et al., 2014). Therefore, further studies should focus on using the PLS-SEM composite model in different fields and techniques. According to Hubona et al. (2021), PLSc is suitable with behavioral data on attitude and trait, while emergent variables are suitable with design variables on capabilities, indicators, and value. They suggest, however, that may generate emergent variables from latent variables.

Limitations and future research

The present study had numerous advantages. However, there were some limitations as follows. Due to budget and time constraints, data from one university may not be sufficient to summarize the outcome's generalizability. The data on intrinsic and extrinsic motivation and job satisfaction in the current study are relevant, leading to a violation of the discriminatory validity of the PLSc. If each construct's data is sufficiently distinct, it can create a PLSc without infringing on the biased validity that could boost the PLSc's reliability.

Conclusions

The current research investigated the relationship between intrinsic and extrinsic motivation and job satisfaction of university workers, including a measure of the extrinsic mediator impact with PLSc and a composite model. The results showed that intrinsic motivation directly affects job satisfaction and has an indirect effect as a complementary extrinsic mediator effect on the composite model. Meanwhile the PLSc generated bias. The current study thus plays a significant role in improving discriminating validity, and not building HCM but condensing the data. However, the latent variables were used to measure behavior, while the emergent variables represented artifact variables. The composite model performed well despite the inclusion of attitude variables in CCA. As suggested by Hubona et al. (2021) confirm that the emergent variable may be built from latent variables.

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