

VRIJE UNIVERSITEIT AMSTERDAM

FACULTY OF SCIENCE

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# Investigating the usefulness of structural equation modelling for service quality in a SaaS delivery model

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RESEARCH PAPER BUSINESS ANALYTICS

*By*

Emils VAVERE

ID No. 2596600

*Under the supervision of:*

Dr. Ger KOOLE

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# Abstract

This research paper looks at the rise of the modern software delivery model Software as a Service or SaaS and the corresponding need to revisit the service quality concept from a SaaS perspective. Structural equation modeling or SEM is used to represent, estimate, and test a model of relationships between unobserved latent constructs and measured variables. SaaS-Qual, which is an instrument for service quality analysis, is used as an example for investigating the usefulness of SEM in a SaaS use case. SaaS-Qual proposes a hypothesised model and relationships between service quality, perceived usefulness, satisfaction and the continuance intention of a SaaS product.

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# Chapter 1

## Introduction

SaaS or Software as a Service is a software licensing and delivery model, where the software is licensed on subscription basis and is hosted centrally - typically cloud-hosted by a third party or self-hosted on a private on-premise cloud.

With the rise of this software delivery model, companies that in the past purchased business critical software on a perpetual licensing basis are now moving to cloud-based, subscription software.

The biggest implication of this move is a shift in responsibilities on deploying and maintaining the software from the software buyer to the software vendor.

Companies now have a reduced risk in software acquisition and a minimized commitment of their resources, which means that they possess the flexibility to stop their subscription without sacrificing costly on-premise infrastructure and IT staff.

For the software vendor this means that they have to maintain and continuously deliver services of the highest quality to try to ensure that their customers will renew their subscriptions.

To understand the service continuance decision making, they have to analyze the service quality facets important to their current customers and potential customers.

The research question proposed for this paper is:

**Investigate the usefulness of structural equation modelling for service quality in a SaaS delivery model.**

This research paper is organized in a couple of chapters to describe how the service quality of a SaaS product can be analyzed with the help of structural equation modelling.

Chapter 2 takes a closer look at the conceptual framework of SaaS delivery model, Service quality concept and its SaaS adaptations.

Chapter 3 focuses on the key concepts of structural equation modelling, the preparatory work needed to be done to conduct SEM analysis.

Chapter 4 focuses on a corresponding study on how SEM is used to construct and validate a SaaS service quality measurement instrument. Also, it is suggested how a SaaS company could use the findings of this research to conduct their own service quality analysis.

Results of this research paper and further research opportunities are discussed in the final Chapter 5.

## Chapter 2

# Service quality in a SaaS delivery model

### 2.1 SaaS delivery model

Service quality is typically understood as the comparison of the customer expectations against the actual service performance delivered to the customer. Research suggests that service quality is a perceived judgement that results from comparing customer expectations with the level of service that customers perceive to have received ([13]).

To better understand how service quality is perceived for solutions delivered as SaaS, we must first take a look at SaaS delivery model itself.

SaaS is a method of deploying software applications as a cloud-hosted service, which is delivered to and accessed by customers over the internet ([7]). This delivery model uses a one-to-many model for software delivery, where a single SaaS provider supplies software services to multiple users.

Some business to business SaaS product examples are Salesforce, HubSpot, Expensify. Typical business to consumer examples are Netflix, Spotify, Amazon Prime. Some example SaaS software tools that are geared for both B2B and B2C are Slack and DropBox.

Under the SaaS delivery model clients are typically billed according to their subscription licensing types and the corresponding software usage patterns, where SaaS clients are required to pay a monthly or annual subscription-based fee to continue using the product.

As the cloud-computing services are accessed online, the SaaS delivery model eliminates the need for client organizations to incur the expense of purchasing and maintaining infrastructure needed to run the application servers and on-premise software themselves ([3]).

This software-delivery mechanism allows customer IT departments to change their focus from deploying and supporting applications, while also ensuring their availability and performance, to having control and enabling effective management.

As these expenses are shifted from the client to the cloud software services provider, organizations have a reduced risk of software acquisition and a minimized upfront commitment of their resources. This delivery model provides the users with more flexibility to discontinue the product usage without having to sacrifice abandoned on-premise infrastructure and IT staff.

The SaaS delivery accompanying subscription model requires the software company to ensure their customer's renewal every renewal period by providing high quality service.

Thus, the relationship between the software provider and the software purchaser becomes a partnership where the customers expect continued support, software upgrades and the ability to affect the future development road-map to ensure continued business benefit from using this software. The software provider has to comply to increase the chances of customer contract renewal and reduce the risk of churn.

The rising complexity of the relationship between the company and the customer, increases the need to find an appropriate instrument for measuring service quality to help identify gaps in the delivered service.

## 2.2 Service quality concept and measurement

Earliest conceptualizations of service quality were built on the confirmation–disconfirmation paradigm - service quality is the extent to which the pre-consumption expectations of quality of the customer are confirmed or disconfirmed by their actual perception of the service received ([9]).

In line with this paradigm, service quality evaluation is the comparison between the expected and received service. Naturally, if the delivered service meets the initial expectations then the customer is satisfied and vice versa.

The most dominant service quality measurement scale is SERVQUAL ([13]). It is a multi-dimensional research instrument, which is designed for capturing consumer expectations and perception of a service in 22 questions along five proposed dimensions that represent service quality:

- Tangibles (4 questions) - Appearance of physical facilities, equipment, personnel, and communication materials;

- Reliability (5 questions) - Ability to perform the promised service dependably and accurately;
- Responsiveness (4 questions) - Willingness to help customers and provide prompt service;
- Assurance (4 questions) - Knowledge and courtesy of employees and their ability to convey trust and confidence;
- Empathy (5 questions) - Caring, individualized attention the firm provides its customers.

A SERVQUAL survey consists of expectations and perceptions part.

In the expectation part the participant is asked about his opinions of banks to understand to what extent the participant thinks banks should possess certain features. The expectations are measured with the help of a Likert scale, where the respondent has to give a quantitative evaluation for 22 questions on a scale ranging from Strongly Disagree to Strongly Agree.

An example question for Expectations from the Tangibles dimension: "Excellent banking companies will have modern looking equipment ([13])".

The perception part of the survey relates to the feelings of the participant towards a particular bank. He is asked to describe the extent of which he believes this bank possesses a particular feature. Again, the answers are given to 22 questions and are measured with the help of the Likert scale.

An example question for Perceptions from the Tangibles dimension: "XYZ bank has modern looking equipment ([13])".

The questions from both parts are matching to enable the author of the survey to calculate the Gap Score for each question pair, which is the difference between Perception and Expectation.

To obtain the unweighted measure of service quality the average Gap Scores are first calculated for each dimension, and then the sum of these is divided by the total number of dimensions.

While SERVQUAL is applicable for surveys across many industries, with typical ones being financial services, education and healthcare, further research should investigate the need to add industry and case-specific dimensions and items to this service quality measurement scale ([18]).

### 2.3 SaaS Service Quality

The robustness of the five dimension SERVQUAL scale has been questioned and some researchers have found that without modification this particular structure is not applicable to the IT industry ([4]).



To overcome some of the shortcomings of the original SERVQUAL scale, another scale based on the "Zones of Tolerance" ([19]) or ZOT measure was proposed ([11], [10]).

This approach suggested utilizing two comparable levels for assessing service quality:

- desired service - the level of service a customer believes can and should be delivered;
- adequate service - the level of service the customer considers acceptable.

The range between these two service levels represents the service performance that the customer expects and considers acceptable, instead of a single point resulting from gap score analysis. Utilizing this method across all dimensions helps in gaining more precise insight about the potential improvement needed, because the author of the survey can now better understand the range of customer expectations for service quality and whether the customer's perception of the performance of the service falls into this range.

When ZOT is used in a survey, the participant is asked to rate the minimum service level, desired service level and his perception of the performance of the service with the help of the Likert scale.

For example, in the SaaS service quality survey conducted by [5] these three corresponding questions were asked in the Rapport dimension:

- When it comes to a shared approach to problem solving my minimum service level is;
- When it comes to a shared approach to problem solving my desired level of service is;
- When it comes to a shared approach to problem solving my perception of the performance of the service is.

With the emergence of the Internet and electronic channels, there have been several adaptations to the SERVQUAL measurement scale. One of these adaptations is a service quality scale for the application service provider (ASP) service provisioning model, which is the predecessor to SaaS. It comprises of a multi-dimension scale: tangibles, reliability, responsiveness, assurance, empathy, trust, business understanding, benefit and risk share, conflict and commitment ([14]).

In an ASP service quality survey conducted by [15] two example questions in the Tangibles dimension are "Our ASP has up-to-date hardware, software and network" and "Our outsourced application interface is visually user appealing and sympathetic".

A key ASP and SaaS difference is that in the ASP model the software applications and the IT infrastructure is dedicated to a single customer, but in SaaS both are shared across multiple customers. This has an effect on system performance, availability and security/privacy aspects.

While the ASP service quality scales are considered the most relevant for measuring service quality in a SaaS context, researchers understanding the uniqueness of the SaaS delivery model have proposed a new service quality measurement instrument for SaaS - SaaS-Qual ([5]).

In the next chapter the construction of the SaaS-Qual scale is used as an example, that proves the usefulness of structural equation modelling for service quality in a SaaS delivery model.

## Chapter 3

# Usefulness of SEM

### 3.1 Key concepts of Structural equation modelling

Structural equation modelling or SEM is used for analyzing survey and research data social, behavioural and health sciences and interpreting the results.

Research in these sciences often contain variables, such as intelligence, cognitive competence, depression, which can't be observed directly. These variables are inferred from other variables that can be observed.

SEM uses hypothesis testing to explore the direct and indirect relationships that occur among these two types of variables:

- latent variables (constructs or factors) - variables that are not directly observable or measured, so they are inferred from a set of observed variables.
- observed (measured, indicator) variables - variables that are directly measured using tests, assessments, surveys, and they are used to define the latent variables ([12]).

Both of these variables can be defined by these two additional types:

- independent variables - a variable that is not influenced by any other variable in the model;
- dependent variables - a variable that is influenced by another variable in the model ([12]).

SEM is a methodology for representing, estimating, and testing a network of relationships between observable variables and latent constructs ([16]). The benefit of using SEM in such cases lie in its ability to impute the relationships between the latent and measured variables.

Another definition states that SEM is used to model and depict relationships between observed variables, with the goal to provide a quantitative test of a theoretical hypothesized model ([12]).

The specification of the custom model has to be based on theory and previous research to help in correctly specifying the relationships between variables ([16]).

A simple case, where SEM could be used, is - a counseling researcher wants to understand the impact of the therapeutic working alliance on the number of counselling sessions the patient will attend. Therapeutic working alliance refers to the relationship between a healthcare professional and a client, and this is a latent construct that can't be directly measured. With the help of SEM the researcher could determine whether the observed variables, such as agreement on the therapy tasks, agreement on the therapy goals, and the counselor-client emotional bond, comprise the construct therapeutic working alliance. SEM could also help understand whether the latent construct therapeutic working alliance can predict the number number of counseling sessions attended by the client ([1]).

Before looking at the actual steps of SEM analysis, we first briefly look at the techniques that contributed to the development of SEM.

The first one was linear regression modeling, which is applied only on observed variables and is used to test a theoretical model that could be useful for prediction. With linear regression modelling a dependent and observed variable is predicted from one or more independent, observed variables ([12]).

Regression models use the correlation coefficient and least squares criterion to estimate the parameters of the model by minimizing the sum of squared differences between observed and predicted scores of the dependent variable ([12]).

A typical example could be where the model is built to predict the impact of observed variables age, gender, diet on a person's heights.

Another foundation piece of SEM is path analysis. It works on predicting relationships among observed variables by solving a series of concurrent regression equations. Path models permit the researcher to test the relationships among multiple independent and dependent variables ([12]).

In an example of path analysis usage, a hypothesis is proposed that a person's age has a direct and positive effect on job satisfaction - the older a person is, the larger the person's job satisfactions, which is our dependent variable. There are also other independent variables, such as autonomy or income, that influence job satisfaction. In path analysis a diagram is used to depict the relationships between the variables - for example, linking age and job satisfaction, age and income, income and job satisfaction. Path analysis solution shows the relationship strength between the variables - for example, proving that autonomy has a stronger link to job satisfaction than age.

Another key model that contributed to the development of SEM, was the confirmatory factor model or CFA. CFA is focused on modeling the relationship between observed and latent variables, and for evaluating the hypothesis about the relationships between latent variables, which in CFA are modeled as covariances/correlations rather than as structural relationships ([12]).

This technique attempts to separate the variance of the observed variable into:

- common variance - proportion of variance that is due to the latent variable;
- unique variance - combination of random error variance;
- reliable variance - specific to a particular item ([8]).

Both CFA and SEM attempt to reproduce the inter-correlations and covariances between the observed variables with a more parsimonious set of latent variables ([8]).

Usage of both CFA and SEM require solid conceptual and empirical foundation to specify every aspect of the models to be evaluated. Typical use cases of CFA are on scale and construct validation.

When developing a new measure a common practice is to first specify an exploratory factor analysis model to evaluate an initial pool of variables, and then conduct CFA to evaluate how a theoretical model represents the observed data ([8]).

CFA is useful for determining the number of latent variables that best represent the theoretical constructs of interest and the pattern of relationships with factor loadings between the observed and latent variables ([8]).

The fact that SEM combines confirmatory factor and path analysis models, allows it to extend the analysis to both observed and latent variables into the same model.

## 3.2 Sequence for conducting SEM Analysis

### 3.2.1 Model specification

The first process of the SEM analysis is the model specification. Ultimately, the analysis results in a consistency comparison between the implied theoretical model and the true model that generated the data.

A theoretical model is deemed consistent, when it sufficiently reproduces the sample covariance matrix, therefore the goal of model specification is to find the best possible model that generates

the sample covariance matrix. This matrix implies some underlying, yet unknown, theoretical model or covariance structure, which the model has to fit closely ([12]).

If differences are found, it indicates a misspecification in the theoretical model. Typically these errors are due to exclusion of key variables or parameters, or due to inclusion of unimportant variables ([12]).

The model specification process is utterly important for the success of the analysis because an implied model that is specified incorrectly may result in a specification error or in estimates that systematically differ from their values in the true model. The resulting theoretical model may not be statistically acceptable and may not fit the data.

Thus, the model specification process must start with a study of relevant theory and research, to raise the chances of correct rationale and reasoning, why a certain variable is included or excluded from the theoretical model and how these variables mutually relate.

For a closer look at the sequence for conducting SEM analysis an example study in the field of counselling research conducted by [1] will be used. In this example the theoretical model attempts to specify the relationship between supervisor multicultural competence and supervisee outcomes, where the model hypothesizes that supervisor multicultural competence:

- directly impacts supervisee counseling self-efficacy (CSE);
- supervisor multicultural competence indirectly impacts supervisee CSE through the supervisory working alliance ([1]).

Another way to depict the hypothesized relationships:

- Supervisor Multicultural Competence - Supervisee CSE;
- Supervisor Multicultural Competence - Supervisory Working Alliance - Supervisee CSE.

The supervisory working alliance mediates the relationship between variable of external cause (exogenous) and variables of internal cause (endogenous).

As SEM models contain both observed and latent variables, the SEM model specification is built in two-steps.

As the first step, the measurement model is specified and the observed variables that are used to define the latent variables are identified. This measurement model does not specify directional relations between the latent variables ([2]).

In this example, the measurement model includes three latent constructs:

- supervisory working alliance, which is estimated by the observed variables - task, goals, bond subscales;
- supervisee CSE, which is estimated by microskills, counseling process, difficult client behaviors, cultural competence, counselor values/biases subscales;
- supervisor multicultural competence ([1]).

This measurement model can be expressed with the help of eight equations. To give a couple of examples:

- Tasks = function of supervisory working alliance + measurement error (from observed variable);
- Goals = function of supervisory working alliance + measurement error ([1]).

If the latent variables are adequately measured by observed variables, the structural model, which specifies the relationships among the latent variables, is specified as the second step ([1]).

In this example, the structural model identifies:

- Direct relationship between supervisee CSE;
- Indirect relationship between supervisor multicultural competence and supervisee CSE through the latent mediator variable supervisory working alliance([1]).

This structural model can also be noted as a series of three equations:

- Supervisee CSE = structure coefficient X Supervisor Multicultural Competence + error;
- Supervisee CSE = structure coefficient X Supervisory Working Alliance + error;
- Supervisory Working Alliance = structure coefficient X Supervisor Multicultural Competence + error.

The three structure coefficients in the structural equations comprise the estimated theoretical covariance matrix. The prediction error term in these equations specify the degree of variance in the latent endogenous variable that is not accounted for by the other variables in the equation ([12]). Also, these equations specify the direction of these predicted relationships.

The theoretical model with the hypothesized relationships between the variables, can be illustrated through a graphical representation with a path diagram depicted in Figure 3.1.

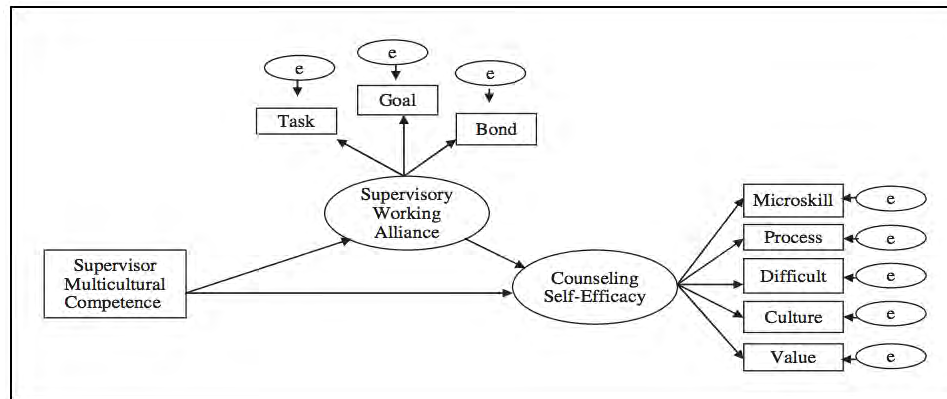


FIGURE 3.1: Path diagram for the theoretical model

### 3.2.2 Model identification

Model identification, which is the second process of SEM analysis, is focused on determining whether there can be a unique solution to the model. This activity occurs prior to estimating the relationships among the variables in the model.

For a model to be considered identified, it must be theoretically possible to find a unique estimate for each parameter ([12]). This activity is dependent on the designation of model parameters:

- free - an unknown parameter that needs to be estimated;
- fixed - a parameter with a specified value, typically 0 or 1;
- constrained - an unknown parameter that is constrained to equal one or more other parameters ([12], [1]).

For the overall SEM to be identified, the measurement model has to be identified first. Previous research has explored that the measurement model with high likelihood can be considered identified when:

- there are two or more latent variables, each with at least three indicators that load on it, the errors of these indicators are not correlated, and each indicator loads on only one factor, or
- there are two or more latent variables, but there is a latent variable on which only two indicators load, the errors of the indicators are not correlated, each indicator loads on only one factor, and the variances or covariances between factors is zero ([1]).

Depending on the amount of information in the sample variance-covariance matrix, which is necessary for uniquely estimating the parameters of the model, research ([12]) typically depicts three levels of model identification:



1. An under-identified model - one or more parameters may not be uniquely determined because there is not enough information in the sample variance-covariance matrix;
2. A just-identified model - all of the parameters are uniquely determined because there is just enough information in the sample variance-covariance matrix;
3. An over-identified model - there is more than one way of estimating a parameter (or parameters) because there is more than enough information in the sample variance-covariance matrix.

To deal with the complexity of establishing whether a structural model is identified, a set of rules is defined for identification of structural models ([12]):

- The recursive rule - for a structural model to be identified it should be recursive or all of the relationships specified by the model should be unidirectional;
- the order rule - the number of free parameters to be estimated must be smaller or equal to the number of distinct values in the sample variance-covariance matrix ([1]).

In simpler terms, the structural model must have more known than unknown pieces of information:

- The number of knowns, which is the number of unique elements in the covariance matrix of the structural model, is calculated by using the formula  $p(p + 1)/2$ , where  $p$  is equal to the number of observed variables.
- The number of unknowns is equal to the number of free parameters to be estimated in the model, which are the relationships between the exogenous and endogenous variables, relationships between the endogenous variables, factor loadings, errors in the equations, variance/covariance of the exogenous variables ([1]).

In the used example, with the help of CFA, it was confirmed that in the measurement model each latent variable had three or more indicators that appropriately loaded on each variable, the errors of the indicators were not correlated, and each indicator in the model only loaded on one factor ([1]).

With visual inspection of the path diagram in Figure 3.1 it is seen that the model is recursive as all relationships specified in the model are unidirectional ([1]).

Also, in this example there are nine observed variables, so the number of knowns in the covariance matrix is 45. The number of free parameters or unknowns to be estimated is 9. So, it follows that the model in the example is over-identified, as the number of unique elements in the covariance matrix exceeded the number of free parameters in the model.

### 3.2.3 Model estimation

The model estimation process is the third process of SEM analysis. Its goal is to estimate the theoretical model parameters in such a way that the theoretical parameter values yield a covariance matrix that is as close as possible to observed covariance matrix.

SEM analysis software uses a fitting function to iteratively minimize the differences between the estimated theoretical covariance matrix and the observed covariance matrix.

There are multiple fitting functions typically used like ordinary least squares, generalized least squares, maximum likelihood.

Covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) are two complementary approaches that are widely used and researched in SEM.

Typically used software for CB-SEM is AMOS, EQS, LISREL, Mplus, while for PLS-SEM typically used software is SmartPLS, SPSS PLS, PLS Graph, R semPLS package ([17]).

In this previous example, maximum likelihood fitting function was used with the help of LISREL to minimize the differences between the estimated theoretical covariance matrix and the observed covariance matrix ([1]).

### 3.2.4 Model testing

The next process after obtaining the parameter estimates is model testing - the goal is to determine how well the theoretical model is supported by the observed sample data.

In model testing both the measurement model and the structural model are analyzed.

First, it must be determined whether the proposed measurement model is sound by checking if the chosen observed indicators for a latent construct actually measure the construct ([1]).

For the previously looked at example, CFA was conducted on the measurement model was run prior to estimating the structural model to ensure that all factors loaded on the latent variables are in the direction expected. The results indicated:

- adequate fit of the CFA model;
- the standardized parameter estimates were significant at the  $p < .05$  level and consistent with the specified hypotheses, loading in the appropriate direction;
- the latent variable supervisory working alliance was significantly positively correlated with its factor indicators;

- the latent variable supervisor CSE was also significantly positively correlated with its factor indicators ([1]).

When the fit of the measurement model is confirmed, the structural model can be analyzed to determine how well the model is supported by the sample data.

The model fit is investigated from two aspects - global fit of the entire model and the fit of individual model parameters. The model-fit criteria is typically based on model implied and sample covariance matrix comparison - if they are similar then the data does fit the theoretical model and vice versa ([12]).

For the fit of individual parameters three key features are considered:

- whether the free parameters are significantly difference from zero;
- whether the sign of the parameter follows the theoretical model expectation;
- whether the values of the parameter estimates are in the expected range ([12]).

For further interpretation of the results of the hypothesized structural equation model:

- when the model-fit indices are acceptable, the hypothesized model has been supported by the sample variance–covariance data;
- when the model-fit indices are not acceptable, it usually attempted to modify the model by adding or deleting paths to achieve a better model to data fit.

In our example, if from the theoretical model it follows that a high level of supervisor multicultural competence leads to an increased supervisee CSE, then a parameter estimate with a positive sign would support this statement.

In the example, SEM analysis was used to determine the fit of the individual parameter estimates and the overall global fit of the entire model. It resulted in:

- fit indices indicated the model was a good fit to the data;
- the path from supervisor multicultural competence to the supervisory working alliance was significant;
- the path from the supervisory working alliance to supervisee CSE was significant;
- the path from supervisor multicultural competence to supervisee CSE was not significant;

- As the path from supervisor multicultural competence to supervisee CSE was not significant, it can be implied that the supervisory working alliance fully mediates the relationship between supervisor multicultural competence and supervisee CSE ([1]).

To further test the chosen structural model, it can also be tested against other alternative models to understand which model best fits the sample data.

### 3.2.5 Model modification

The final process in the SEM analysis is model modification - the goal is to modify the theoretical model and restart the evaluation process of the re-specified model in cases where the model fit is not strong enough.

Model modification suggests multiple actions, called the specification search, that help in the detection of errors in the specification, e.g. if the model contains a parameter that has no substantial meaning for the research, then the resulting model would lose practical applicability ([12]).

No single procedure will be sufficient to ensure that the model will be correctly specified, so SEM applications usually include multiple informal or formal specification search activities, such as

- considering statistical significance of estimated parameters and weighing it against the reasoning, why it was initially included in the model;
- understanding the misspecification through examination of the standardized or unstandardized residual matrix;
- investigating the modification indexes for non-free parameters;
- investigating the measurement equations to understand the squared multiple correlation for the observed variables;
- investigating the expected parameter change ([12]).

## Chapter 4

# SaaS-Qual instrument

As the goal of this research paper is to investigate the usefulness of structural equation modelling for service quality in a SaaS delivery model, the following sections reference and take a closer look at the research done by ([5]) in building the SaaS-Qual service quality instrument with the help of structural equation modelling.

The three key steps were:

1. conceptual development of the research model and initial survey question pool generation;
2. conceptual refinement of the model, question modification and conducting of the pilot survey;
3. conducting the main survey and analyzing it's results ([5]).

### 4.1 Research Model and Hypotheses Development

The foundations of the research model and the corresponding hypotheses for the construction of the SaaS-Qual instrument were found in the theory of IS continuance, which describes the IS usage behavioral patterns after its adoption. Research suggests that IS post-adoption at an organization corresponds to the three final phases (acceptance, routinization, infusion) of a six-stage IS implementation model ([6]).

Following studies develop the post-acceptance model for IS continuance based on expectation-confirmation theory corresponding to customer satisfaction - IS users continuance decisions are influenced by the initial use and missed expectations may lead to the discontinuance of the IS ([6]).

This model doesn't fully describe user expectation system performance and service level measures, thus a more in-depth service quality conceptualization is needed to incorporate more specific service quality factors that influence customer satisfaction and inform the service providers on the importance of different SaaS service quality drivers ([5]).

In order to increase the diagnostic value of the aforementioned model ([6]) it is enriched by an antecedent variable - Confirmation of SaaS service quality.

This new element is refined and conceptually informed by the ZOT-based IS SERVQUAL and SaaS literature and captures all of the identified and validated SaaS service quality dimensions ([5]).

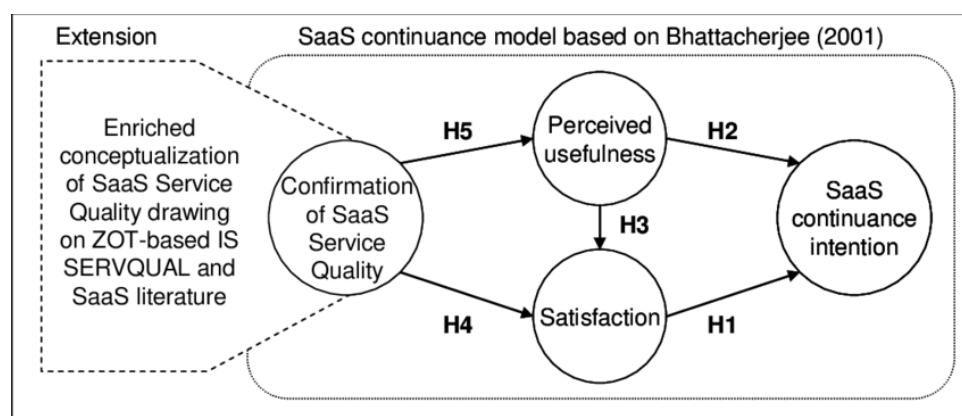


FIGURE 4.1: SaaS continuance model based on Bhattacharjee (2001)

The model depicted in Figure 4.1 is used as the research model for developing the SaaS-Qual instrument. The rationale for the built-in model relationships stems from the previous study by ([6]) that in the context of IS continuance the satisfaction with an IS tends to reinforce a user's intention to continue using the IS system, and similarly the same argument is applicable to the continuance intention of SaaS users ([5]).

These are the corresponding hypothesis proposed by ([5]):

- H1: Satisfaction has a positive association with SaaS continuance intention.
- H2: Perceived usefulness has a positive association with SaaS continuance intention.
- H3: Perceived usefulness has a positive association with satisfaction.
- H4: Confirmation of SaaS service quality has a positive association with satisfaction.
- H5: Confirmation of SaaS service quality has a positive association with perceived usefulness.

## 4.2 Research Methodology

For testing the research model and validating the new measurement instrument ([5]) conducted a data collection phase, where two survey questionnaires were designed and conducted. The data was drawn from a database of SaaS using firms representing various industries and sizes.

The target respondent group were people in the managing roles of the IS related departments of the firms. Aligned with the "key informants" methodology, these people were asked questions corresponding to the more high-level organizational properties.

First survey was used for refining the service quality instrument and for factorial validation - it contained only the SaaS service quality questions. This was sent to 1000 companies, and 111 responses were usable.

Second survey was used for conducting confirmatory analysis of the measurement properties and testing the proposed hypotheses for the research model - these questions spanned all factors of the research model. This was sent to 2000 companies, and 172 responses were usable.

To gain confidence about the validity of the results of the survey, analysis was done on self-reporting bias, non-response bias and demographics (SaaS usage length and frequency, industry, application types).

For common-method bias these two tests were conducted:

- Harman's one-factor test with exploratory factor analysis on all variables showed that no single factor influenced the majority of the covariance.
- Correlational marker technique showed that inclusion of the highest variable from the factor analysis as an additional independent variable, did not create a notable change in the dependent variable variance.

All the conducted analysis showed that the gathered data is usable for further testing of the proposed research model ([5]).

## 4.3 Measurement of Constructs and Instrument Validation

Prior service quality measurements were used by [5] as conceptual basis for building their SaaS service quality instrument. Given the specifics of SaaS, further scale development process was conducted following the steps summarized in Figure 4.2.

The third and fourth step of this process were based on the data from the first survey, but fifth, sixth and seventh steps with data from the second survey.

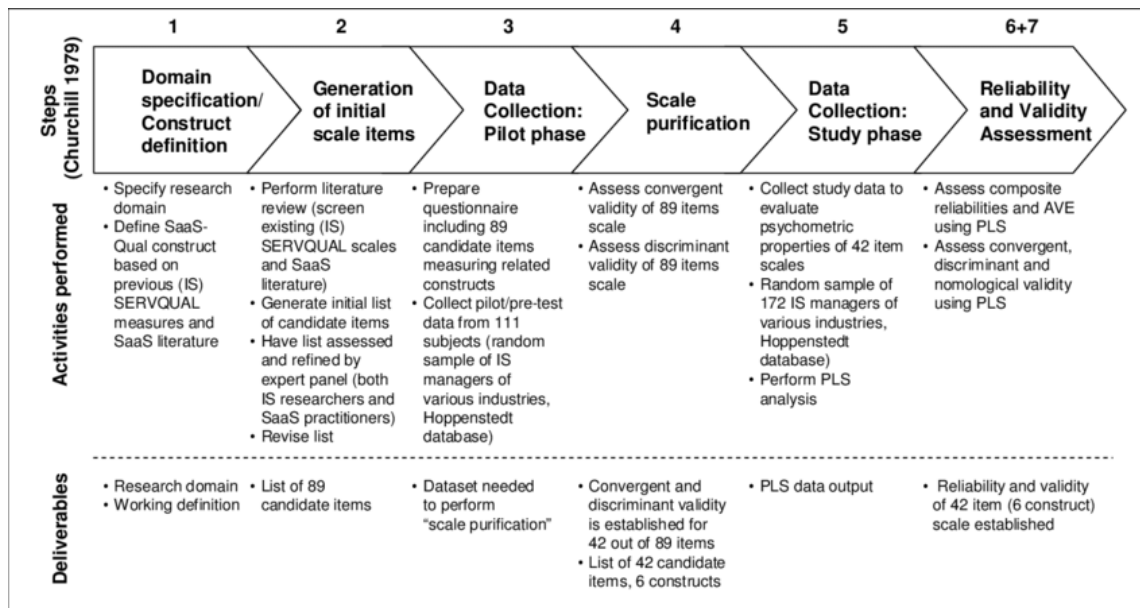


FIGURE 4.2: Scale development process steps ([5])

The resulting list contains 42 items in these 6 corresponding dimensions ([5]) of SaaS service quality:

- **Rapport** - includes all aspects of a SaaS provider's ability to provide knowledgeable, caring, and courteous support (e.g. joint problem solving or aligned working styles) as well as individualized attention (e.g. customer-specific trainings and courses).
- **Responsiveness** - consists of all aspects of a SaaS provider's ability to ensure that the availability and performance of the SaaS-delivered application (e.g. through professional disaster recovery planning or load balancing) as well as the responsiveness of support staff (e.g. 24x7 hotline support availability) is guaranteed.
- **Reliability** - comprises all features of a SaaS vendor's ability to perform the promised services dependably and accurately (e.g. providing services at the promised time).
- **Flexibility** - refers to the degrees of freedom customers have to change contractual (e.g. cancellation period or payment model) or technical (e.g., scalability of storage capacity, individual modifications to the application service) aspects in the relationship with a SaaS vendor.
- **Features** - refers to the degree the key features and functionalities (such as data extraction or application type specific functionality) of a SaaS application meet the business requirements of a customer.
- **Security/Privacy** - includes all aspects to ensure that regular (preventive) measures (e.g. regular security audits, usage of encryption or anti-virus technology) are taken to avoid data breaches or system outages.



## 4.4 Construct measurement and validation

The research model proposed by ([5]) has four constructs with measurement items that were validated in previous studies and the aforementioned scale development process:

- SaaS service quality - formative second-order construct with six reflective first-order constructs;
- Satisfaction - reflective first-order construct;
- Perceived usefulness - reflective first-order construct;
- SaaS continuance intention - reflective first-order construct.

For confirming SaaS service quality ([5]), actual performance and minimum accepted service quality difference scores from the ZOT approach were used as measurement items. The remaining constructs were measured with help of a seven-point Likert scale.

The psychometric property analysis is summarized in Figure 4.3.

Constructs	# of indicators	Range of Loadings <sup>1</sup>	Cronbach's alpha	Composite Reliability ( $\rho_c$ )	AVE
Rapport <sup>2</sup>	9	0.79 – 0.96	0.93	0.95	0.83
Responsiveness <sup>2</sup>	9	0.86 – 0.97	0.98	0.99	0.87
Reliability <sup>2</sup>	5	0.81 – 0.96	0.92	0.93	0.83
Flexibility <sup>2</sup>	6	0.87 – 0.96	0.96	0.97	0.86
Features <sup>2</sup>	7	0.94 – 0.97	0.95	0.98	0.92
Security <sup>2</sup>	6	0.70 – 0.95	0.97	0.98	0.77
SaaS continuance intention	3	0.84 – 0.87	0.86	0.89	0.73
Satisfaction	4	0.94 – 0.97	0.97	0.98	0.92
Perceived usefulness	4	0.87 – 0.92	0.92	0.94	0.81

<sup>1</sup> All factor loadings are significant at least at the  $p < 0.05$  level;

<sup>2</sup> All SaaS-Qual constructs were measured based on difference scores between perceived and minimum accepted service levels

FIGURE 4.3: Psychometric property analysis ([5])

Overall, ([5]) analyzed these facets of the research model:

- Individual item loadings - loadings of the measurement items and their corresponding factors were significant and above the threshold value of 0.70;
- Discriminant validity - cross-loadings on the unintended constructs were not larger than 0.4;
- Internal consistency - for all reflective constructs the 0.70 threshold was exceeded;
- Convergent validity - adequate, when average variance extracted (AVE) is above 0.50.

For the discriminant validity to be satisfactory, the square root of the AVE from the construct should be greater than the variance shared between the construct and other constructs in the model ([5]).

Figure 4.4 depicts discriminant validity with the correlation matrix among the constructs and with the square root of AVE on the diagonal.

Latent construct	1	2	3	4	5	6	7	8	9
(1) SaaS cont. intention	<b>0.85</b>								
(2) Satisfaction	0.50***	<b>0.96</b>							
(3) Perceived usefulness	0.60***	0.26**	<b>0.90</b>						
(4) Rapport	0.33**	0.56***	0.21*	<b>0.91</b>					
(5) Responsiveness	0.35**	0.66***	0.19*	0.54***	<b>0.93</b>				
(6) Reliability	0.20*	0.54***	0.19*	0.51***	0.59***	<b>0.91</b>			
(7) Flexibility	0.22*	0.62***	0.17*	0.49**	0.51***	0.42**	<b>0.93</b>		
(8) Features	0.12 <sup>ns</sup>	0.36**	0.25**	0.42**	0.43**	0.43**	0.41**	<b>0.96</b>	
(9) Security	0.16 <sup>ns</sup>	0.64***	0.26**	0.47**	0.43**	0.49***	0.48***	0.41**	<b>0.88</b>

Note: Bolded diagonal elements are the square root of average variance extracted (AVE). These values should exceed inter-construct correlations (off-diagonal elements) for adequate discriminant validity. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ ; ns=not sign.

FIGURE 4.4: Correlation matrix ([5])

For measurement models that involve emergent constructs the quality assessment is conducted by examining the item weights. For the formative second-order model of SaaS-Qual, ([5]) modelled the coefficients of each first-order factor to the second-order factor by using the principal component factor analysis. Correlation matrix in Figure 4.4 validates the expected relationship between the corresponding first and second order factors, as the first-order quality factors are correlated and significantly different from zero.

As ([5]) found, when the correlation between the first-order constructs are below the cut-off value of 0.90, then the unique distinction between the first-order factors indicate discriminant validity.

Additionally, by using PLS it was tested that the SaaS-Qual construct mediates the first-order facet impact on customer satisfaction. This result indicates that this construct is a more parsimonious representation of the corresponding first-order constructs and captures their predictive power on the dependent variable it is theorized to predict ([5]).

## 4.5 Structural equation modelling results

To test the relationships between the constructs of the model, ([5]) used SmartPLS - structural equation modelling software. Figure 4.5 depicts the results of SEM.

Overall, the proposed research model with the enriched conceptualization of SaaS service quality was supported.

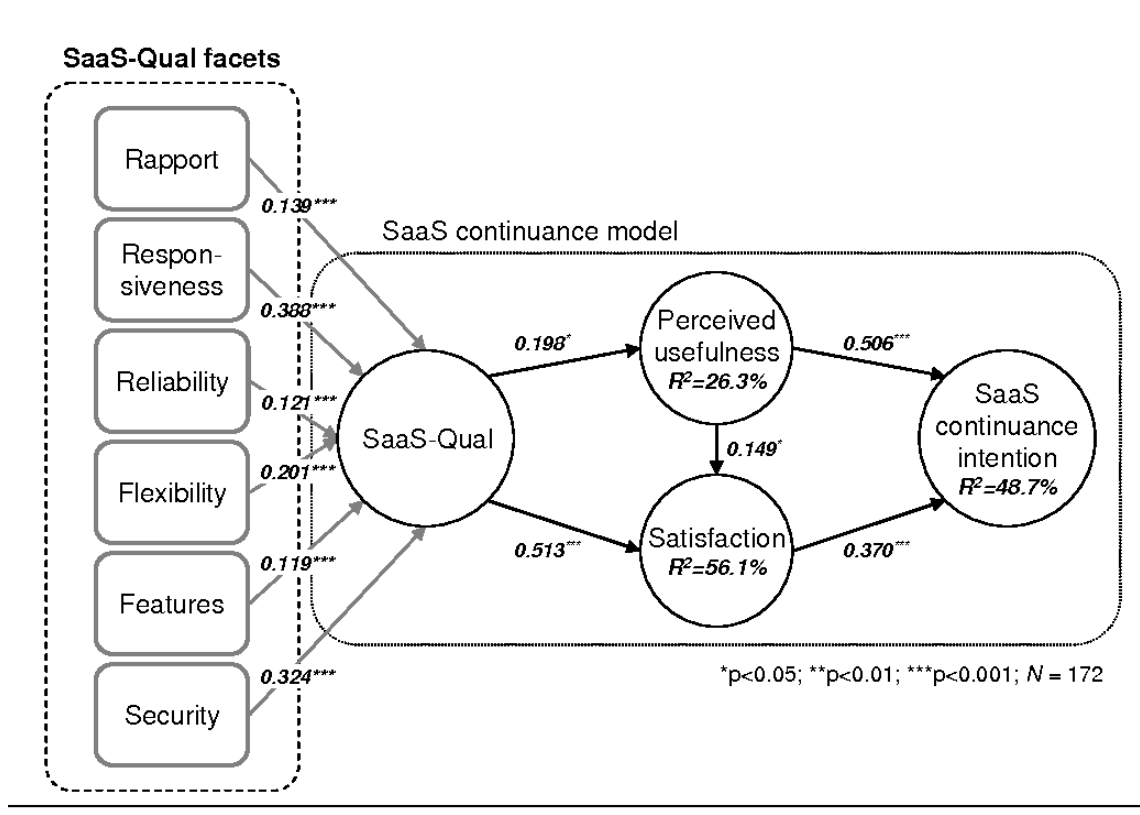


FIGURE 4.5: Structural Equation Modelling results ([5])

First, the coefficients are in the appropriate direction and all are statistically significant.

Second, the model explains a considerable portion of the variance in SaaS continuance intention, satisfaction, and perceived usefulness. These results attest to SaaS-QUAL's predictive validity. In an alternative structural model, ([5]) tested direct link between SaaS service quality confirmation and SaaS continuance intention and confirmed that the former did not have a significant effect on the latter, suggesting that its effect is fully mediated by perceived usefulness and satisfaction.

Third, Responsiveness and Security/Privacy are the strongest factors contributing to SaaS service quality's impact on satisfaction and perceived usefulness, which match the results from the Zones of Tolerance analysis.

## 4.6 Service quality analysis with SEM at a specific SaaS company

This research paper has gathered a couple of lists of step-wise activities for analyzing service quality, building the SaaS-Qual instrument, conducting SEM analysis.

Before engaging in these a SaaS company has to decide on the business reasoning for dedicating resources for this. For example, the research done by [5] suggest to analyze service quality to better understand the facets important to the SaaS customer and how they relate to their intent of continuing using the SaaS product. The resulting confirmed SaaS continuance model can now be used to regularly and efficiently survey the customer base knowing what constructs are important to measure.

Each research is unique therefore a SaaS company has to use theory and prior research to guide the new model specification process that would best describe their business issue at hand and the specifics of the industry the SaaS vendor is operating in.

## Chapter 5

# Discussion

To capture the usefulness of structural equation modelling for service quality in a SaaS delivery model, this research looked at SaaS delivery model, service quality concept and an example on how structural equation modeling is used to build a SaaS-Qual instrument for analyzing the impact of service quality and the corresponding constructs on service continuance intention.

It is clear that structural equation modelling is not just a statistical tool for testing the relationships between measured and latent variables. SEM requires a formal specification of a model, which is based on previously defined research hypotheses and relations between variables.

The usefulness of SEM is tied to the fact that it is a methodology that guides the research by emphasizing the importance of studying prior research and theory to correctly represent and estimate this relationship network.

Another key benefit of using SEM is that it allows incorporating both observed and latent variables, and the graphical modelling allows an easy-to-use way to observe complex relationships.

SEM is useful for SaaS companies looking to investigate the quality of their service, as SEM methodology helps in analyzing research data and interpreting its results.

Further research on testing and potentially further refining the SaaS-Qual instrument in a specific SaaS company, would further confirm and emphasise the role of SEM in the SaaS service quality context.

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