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ORIGINAL ARTICLE

Does culture matter? Corporate reputation and sustainable satisfaction in the Chinese and German banking sector

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Abstract
Corporate reputation is important for all types of banks across the world, despite these countries differing culturally. Building on an extended corporate reputation model, we identify the key drivers of customer-based reputation and sustainable customer satisfaction in two culturally different countries, namely China and Germany. We also consider two reputation dimensions—perceived competence and likeability—and their effects on the target construct. Empirical data from 625 German and 734 Chinese commercial bank customers allow us to estimate the corporate reputation model with the partial least squares structural equation modeling (PLS-SEM) method, and by substantiating the relationships by means of a necessary condition analysis (NCA) and a predictive power analysis. By comparing the two countries' results, we identify their cultural differences. Overall, we confirm the model's relevance for the two cultures, finding that banks' perceived attractiveness is the most important driver of both cultures' customer-perceived bank reputation. By means of an importance-performance map analysis, we identify a large overlap between the two cultures' set of important constructs, likeability's much greater importance in Germany, and the perceived quality construct's relevance in both countries. We contribute to research and scientific knowledge about corporate reputation models by identifying the similarities in and differences between two countries' markets with respect to the banking sector, all of which have implications for international banks' management.

Keywords Customer-perceived reputation · Sustainable satisfaction · Commercial banks · PLS-SEM

Introduction

Prior research has shown that companies rely on a positive corporate reputation (Otto et al. 2020), which has proved to enhance their competitive advantage potential (Gray and Balmer 1998). Several studies have confirmed the positive relationship between corporate reputation, customer satisfaction (Walsh and Beatty 2007), and loyalty (Ali et al. 2015). Since banks rely greatly on their customers' trust, their corporate reputation is especially important for them (Englert et al. 2020). Further, banks struggle to differentiate themselves, which means their reputation is an important intangible resource. Research also suggests that Asia and Europe regard bank reputation differently (Zhang and Schwaiger 2012). In addition, prior research suggested that, in general, there is a difference in low-context and high-context cultures' customer behavior.

We therefore collected data from China, a high-context culture, and Germany, a low-context culture, for our study. Nienaber et al.'s (2014) study results indicated that reputation is more important in terms of trust in a bank in Asia's

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banking sector than in Europe's one. Consequently, we presumed that our Chinese and German subsamples' perceptions of reputation and sustainable satisfaction differed. Our study's purpose was to undertake a deep dive into the respective differences to derive theoretical implications for future research and practical implications for bank managers in Asia and Europe.

The last two decades have seen various transformations in the banking services. Specifically, commercial banks' aim is to provide their customers with professional, scenario-based, and uninterrupted smart service experiences. New technologies and digital transformation have also had a strong impact on financial institutions, forcing them to change their business models rapidly (Hopkinson et al. 2019). Simultaneously, customers' consumption behavior has shifted to electronic contact with no direct personal contact (Bartmann et al. 2013). The latter has led to customer loyalty toward physical bank branches decreasing gradually (Li et al. 2021). Relatively new forms of bank innovation, such as unmanned branches and smart banks, have forced commercial banks to improve their customer experience through various financial technologies and new devices to achieve the best service marketing effects (e.g., Tseng et al. 2021). In addition, competition in the banking sector has become fierce, with new competitors, such as internet companies, fintech companies, and self-operated financial service platforms, emerging continually (e.g., Vives 2017).

Nevertheless, the lack of customer satisfaction is one of the main reasons for customers switching banks (Chakrabarty 2004; Manrai and Manrai 2007). This dissatisfaction is often due to the increasing costs (Colgate and Hedge 2001; Manrai and Manrai 2007; Santonen 2007), motivating customers to switch to banks offering better value for money. The irony is that, given their competitive market, banks cannot afford to lose customers, since a net loss of customers is closely linked to a loss of profits and market share (Manrai and Manrai 2007). Customer churn is therefore of great importance for retail banking's service areas (Sweeney and Swait 2008).

Commercial banks in China and Germany are our research object, which allows us to compare the same type of bank in both countries. The German banking sector comprises three pillars: commercial banks, cooperative banks, and savings banks. The commercial banking sector accounted for 22.9% of the market share in 2020 (Bundesbank 2021). In China, commercial banks include national commercial banks, urban commercial banks, rural commercial banks, and foreign banks. The first three are mostly state-owned enterprises. In addition to competing with one another, Internet finance companies, such as Alibaba, have greatly impacted these commercial banks' business (Dong et al. 2020).

Building on prior corporate reputation research in the banking sector (section "Corporate bank reputation and sustainable customer satisfaction"), we strive to answer the following research question: *What are the drivers of commercial banks' corporate reputation and sustainable satisfaction in China and Germany*? We build on an a priori validated path model to answer this question and collect two representative samples of Chinese and German commercial bank customers, which we subsequently evaluate by means of partial least squares structural equation modeling (PLS-SEM; Lohmöller 1989; Wold 1982). This method not only allows us to assess the models in both countries, but also to conduct further analyses for comparison purposes and for an importance-performance map analysis (IPMA), thereby allowing us to derive practical implications.

More specifically, our study makes the following contributions: First, although prior research examined similar models to explain bank customers' thoughts on their bank's reputation, their satisfaction with their bank, and their loyalty, no existing studies have as yet investigated the specific similarities and differences between customers in low- and high-context cultures' perceptions, using comparable datasets. By doing so, we offer bank managers practical advice that could help them make evidence-based decisions on how to attract and maintain relationships with their customers in an international context. Second, from a more theoretical perspective, we offer a simplified reputation model that combines customer satisfaction and loyalty in one construct, which maintains that long-term satisfaction and loyalty are needed for sustainable customer-bank relationships. Third, from a methodological perspective, we not only compare datasets by applying a single method (PLS-SEM), but also complement our analysis with complementary analysis methods, such as a necessary condition analysis (NCA) and an IPMA.

We organize our article as follows to address our research question and present our research contribution: section "Corporate bank reputation and sustainable customer satisfaction" describes bank reputation and the sustainable satisfaction model's development. In section "Data and method", we describe the data and method used to build the sustainable satisfaction model for China and Germany. Our assessment of the empirical results, which include an NCA and IPMA, follows in section "Results assessment". The study concludes with section "Discussion", which describes the main findings and our conclusions regarding marketing research, the study's practical implications, and future research directions.

Corporate bank reputation and sustainable customer satisfaction

In this study, we examine commercial bank customers' perception of bank reputation and sustainable (i.e., long-term) satisfaction in China and Germany. Customer-based reputation is defined in various ways. Since we focus on the customer perspective, we follow Walsh and Beatty's (2007) definition that "the customer's overall evaluation of a firm is based on his or her reactions to the firm's goods, services, communication activities, interactions with the firm, and/or its representatives or constituencies (such as employees, management, or other customers), and/or its known corporate activities" (Walsh and Beatty 2007, p. 129). We test Schwaiger's (2004) corporate reputation model in both countries, using sustainable (long-term) customer satisfaction as the target construct (Damberg 2021).

Bank reputation is a particularly interesting and important topic in the strategic marketing field (Boonlertvanich 2019; Bugandwa et al. 2021; Damberg et al. 2022; Zhang and Schwaiger 2012), because corporate reputation has a positive influence on customer satisfaction and loyalty, which could give a bank a competitive advantage and/or increase its performance (Otto et al. 2020). Prior literature focusing on consumer behavior and perceptions found that corporate reputation's affective dimension contributed more to customers' potential loyalty than its cognitive reputation dimension did (Schwaiger et al. 2021). Moreover, in Germany, positive public corporate reputation perceptions have shown to be positively related to shareholder value when measured by means of future stock returns (Raithel and Schwaiger 2015).

Various authors have tried to operationalize a company's reputation, which is a latent, not directly observable, variable. Further, prior research also applied and validated Schwaiger's (2004) two-dimensional corporate reputation (Sarstedt and Schloderer 2010; Schloderer et al. 2014; Schwaiger et al. 2009) in different countries (Damberg 2021; Eberl 2010; Zhang and Schwaiger 2012).

For the purpose of this study, and in accordance with Schwaiger (2004), customer-perceived bank reputation is modeled as a two-dimensional construct comprising perceived competence (COMP) as a cognitive dimension, and perceived likeability (LIKE) as an affective dimension. This modeling approach allows researchers to identify the overall concept's specific effects on the lower-order (i.e., LIKE and COMP) dimensions (Sarstedt et al. 2019). In Schwaiger's (2004) original model, corporate reputation has four antecedents that influence the reputation levels, namely the perceived quality (QUAL), performance (PERF), corporate social responsibility (CSOR), and the company's perceived attractiveness (ATTR). According to previous studies' findings, both of corporate reputation's dimensions (i.e., COMP and LIKE) have a positive influence on customers' (more short-term oriented) satisfaction and long-term loyalty, with the latter modeled as the target construct. In our reputation model, we use a single target construct, namely sustainable satisfaction (SUSSAT), which is a combination of customer satisfaction and loyalty, and was first applied in the German cooperative banking context (Damberg 2021). Prior research argued that it is not always possible to distinguish clearly between the satisfaction and loyalty constructs (e.g., Kocyigit and Ringle 2011). In Kocyigit and Ringle's study, the construct sustainable brand satisfaction comprises combining items from the satisfaction and loyalty scales into a single target construct, which Höck et al. (2010) introduced. We therefore adapted the sustainable brand satisfaction scale's items to fit the banking context. We used this single target construct that allowed us to better create a less complex and more focused model.

The theoretical model tested in this study is built on the constructs and their relationships, which Schwaiger (2004) and Damberg (2021) described. The four constructs—QUAL, PERF, CSOR, and ATTR,—all of which have a formative measurement model (e.g., Schwaiger 2004; Table 1), represent the antecedents and the drivers of the two corporate reputation dimensions COMP and LIKE, each of which have a reflective measurement model (e.g., Schwaiger 2004; Table 1). The structural model focuses on analyzing how the corporate reputation dimensions influence and explain the target construct, SUSSAT, which—as Damberg (2021) showed—has a reflective measurement model; see also Table 1.

In line with the research that Schwaiger (2004) and Damberg (2021) presented, Fig. 1 illustrates the theoretically established model with its constructs and relationships. Table 2 displays the theoretically established hypotheses of the relationships in this model. Based on empirical data, we examine the extent to which these hypothesized relationships can be confirmed in terms of China and Germany, therefore validating the theoretically established model empirically. In addition, the empirical examination allows us to determine which of the drivers of the two corporate reputation dimensions are specifically important in which country and are primarily relevant for SUSSAT.

Data and method

The operationalization of our reputation model's constructs was tested in previous studies (Table 1), establishing its validity and reliability irrefutably. The items were

Table 1 Measurement and operationalization

Formative constructs	Items	Sources
Perceived quality (QUAL)	QUAL1: My primary bank always pays great attention to my concerns QUAL2: The range of services that my bank offers is in line with my needs QUAL3: I consider my bank a trustworthy company QUAL4: The products and services that my bank offers are of high quality QUAL5: I think that the products and services that my bank offers are good value for money QUAL6: In my opinion, my bank is a pioneer rather than a follower competing with other banks	Damberg (2021), Damberg et al. (2022), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Perceived performance (PERF)	PERF1: My main bank is an economically stable company PERF2: My main bank is a well-managed company PERF3: I consider my main bank's economic risk to be low compared to that of its competitors PERF4: My main bank seems to have a clear vision of the company's future PERF5: I believe that my main bank has the potential to grow	Damberg (2021), Damberg et al. (2022), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Perceived corporate social responsibility (CSOR)	CSOR1: I believe my main bank is not only interested in profit CSOR2: My main bank is also committed to preserving the environment CSOR3: My main bank behaves responsibly toward society CSOR4: I believe that my main bank informs the public honestly CSOR5: I believe that my main bank behaves fairly toward its competitors	Damberg (2021), Damberg et al. (2022), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Perceived attractiveness (ATTR)	ATTR1: My bank is an attractive company ATTR2: I like my bank's appearance (its branches, logo, website, etc.) ATTR3: In my opinion, my bank employs highly qualified staff ATTR4: I could well imagine working for my bank	Damberg (2021), Damberg et al. (2022), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Reflective constructs	**Items**	**Sources**
Perceived competence (COMP)	COMP1: My primary bank is a leading provider in the market COMP2: As far as I know, my personal bank has a good reputation COMP3: In my opinion, highly qualified employees work at my personal bank	Damberg (2021), Damberg et al. (2022), Raithel and Schwaiger (2015), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Perceived likeability (LIKE)	LIKE1: I identify more with my personal bank than with others LIKE2: If my personal bank no longer existed, I would regret this more than I would regret other banks' disappearance LIKE3: I feel that my personal bank values me as a customer	Damberg (2021), Damberg et al. (2022), Raithel and Schwaiger (2015), Schloderer et al. (2014), Schwaiger et al. (2009), Schwaiger (2004)
Sustainable satisfaction (SUSSAT)	SUSSAT1: My personal bank meets my expectations SUSSAT2: I will remain a customer of my personal bank in the future SUSSAT3: I would recommend my personal bank to my friends and family	Damberg (2021), Damberg et al. (2022), Schwaiger et al. (2009), Schwaiger (2004)

Source All items were measured on a Likert-scale from 1 (do not agree at all) to 7 (fully agree)

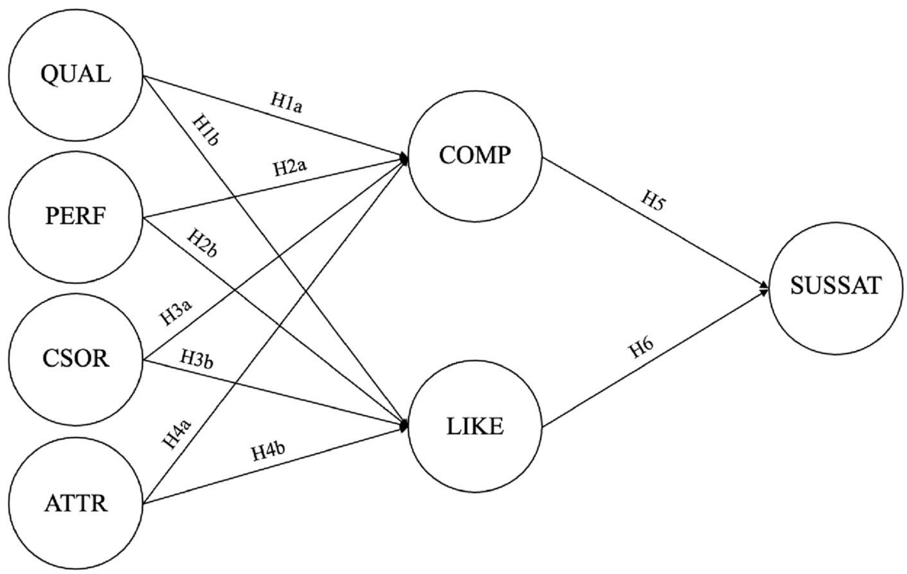

Fig. 1 Theoretical model (based on Damberg 2021). *QUAL* perceived quality; *PERF* perceived performance; *CSOR* perceived corporate social responsibility; *ATTR* perceived attractiveness; *COMP* perceived competence; *LIKE* perceived likeability; *SUSSAT* sustainable satisfaction

Table 2 Hypotheses

Hypothesis	
H1a	Higher levels of perceived quality lead to higher levels of the customer-perceived reputation's cognitive dimension (i.e., perceived competence)
H1b	Higher levels of perceived quality lead to higher levels of the customer-perceived reputation's affective dimension (i.e., perceived likeability)
H2a	Higher levels of perceived performance lead to higher levels of the customer-perceived reputation's cognitive dimension (i.e., perceived competence)
H2b	Higher levels of perceived performance lead to higher levels of the customer-perceived reputation's affective dimension (i.e., perceived likeability)
H3a	Higher levels of perceived corporate social responsibility lead to higher levels of the customer-perceived reputation's cognitive dimension (i.e., perceived competence)
H3b	Higher levels of perceived corporate social responsibility lead to higher levels of the customer-perceived reputation's affective dimension (i.e., perceived likeability)
H4a	Higher levels of perceived attractiveness lead to higher levels of the customer-perceived reputation's cognitive dimension (i.e., perceived competence)
H4b	Higher levels of perceived attractiveness lead to higher levels of the customer-perceived reputation's affective dimension (i.e., perceived likeability)
H5	Higher levels of customer-perceived reputation's cognitive dimension (i.e., perceived competence) lead to commercial bank customers' increased levels of sustainable customer satisfaction
H6	Higher levels of customer-perceived reputation's affective dimension (i.e., perceived likeability) lead to commercial bank customers' increased levels of sustainable customer satisfaction

respectively translated (and back translated) into German and Chinese. We measured all the constructs on a Likert scale ranging from 1 (do not agree at all) to 7 (fully agree). All the items were previously adapted to and validated in the banking context (Damberg 2021; Damberg et al. 2022). The data collection largely followed the process that Sarstedt et al. (2023b) described for obtaining corporate reputation model data. Since all the questions in the online surveys were mandatory, we did not have to undertake a missing value analysis. More precisely, the German subsample was collected via the market-research institute Respondi, with the objective of ensuring that the target population's representation (i.e., German commercial banks' customers). The Chinese subsample was obtained from Chinese banks' WeChat groups, through which famous commercial banks, such as the Bank of China, Bank of Communications, and Industrial and Commercial Bank of China, promote their products and banking services.

Our final sample comprised responses from 734 Chinese and 616 German commercial bank customers. Table 9 in the Appendix shows the descriptive statistics. We ensured PLS-SEM's technical suitability in respect of each country-specific sample's size. We used the inverse square root method (Kock and Hadaya 2018) to determine the sample size needed to achieve a certain level of statistical power. For example, one would need approximately 619 observations to render the corresponding effect significant at 5%, if one were to assume that the minimum path coefficient expected to be significant is between 0.05 and 0.1 (Hair et al. 2022).

We estimated the reputation model by using PLS-SEM (Lohmöller 1989; Wold 1982), a variance-based multivariate analysis method aimed at maximizing the amount of the dependent constructs' and/or the indicators' explained variance (Hair et al. 2022). For a recent update on the PLS-SEM method's discussions see, for example, Cook and Forzani (2023), Petter and Hadavi (2021), and Russo and Stol (2023). Since this research method's main objective is to test a theoretical framework and to explain and predict a target construct (i.e., SUSSAT), we assumed that the constructs in our model's arrangement is of a causal-predictive nature (Chin et al. 2020; Hair et al. 2019). Besides PLS-SEM's characteristics and distinguishing features (for further details, see Sarstedt et al. 2023a), which support our research's goal, PLS-SEM also allows researchers to estimate reputation models that include both formatively and reflectively measured constructs (Sarstedt et al. 2021)—as in our research. Moreover, the PLS-SEM method allows us to extend existing theories and develop new ones (Richter et al. 2016). PLS-SEM has therefore been successfully applied in marketing research and is a widely established method in the social sciences (Sarstedt et al. 2021, 2022). We applied the SmartPLS 4 software (Ringle et al. 2022), whose use in research studies is well established (Sarstedt and Cheah 2019), to estimate our reputation model with the collected empirical data.

Results assessment

The measurement model's assessment follows Hair et al. (2019, 2022) and Sarstedt et al. (2021)—for extended and advanced PLS-SEM analyses see, for example, Becker et al. (2023), Guenther et al. (2023), Hair et al. (2024), and Sarstedt et al. (2020). We report the bias-corrected results of the percentile bootstrapping approach with 10,000 subsamples and a two-tailed 95% confidence interval for significance testing. We assess the reflective measurement models by analyzing their indicator reliability, internal consistency, convergent validity, and discriminant validity. All the indicator loadings are significantly above the recommended threshold of 0.7 (Table 3). Cronbach's α and ρ_A allow us to evaluate the reflective constructs' internal consistency reliability. All the results are again above the threshold value of

Table 3 Indicator loadings, reliability, and convergent validity

Constructs	Indicators	Loadings	Cronbach's α	ρ_A	AVE
China					
COMP	COMP1	0.814 [0.782;0.841]	0.734 [0.693;0.769]	0.734 [0.693;0.769]	0.653 [0.619;0.684]
	COMP2	0.802 [0.761;0.835]			
	COMP3	0.807 [0.774;0.835]			
LIKE	LIKE1	0.802 [0.769;0.828]	0.710 [0.662;0.749]	0.715 [0.667;0.753]	0.632 [0.595;0.665]
	LIKE2	0.772 [0.715;0.813]			
	LIKE3	0.810 [0.776;0.838]			
SUSSAT	SUSSAT1	0.818 [0.779;0.847]	0.731 [0.687;0.771]	0.733 [0.687;0.771]	0.650 [0.615;0.686]];
	SUSSAT2	0.787 [0.738;0.822]			
	SUSSAT3	0.814 [0.781;0.841]			
Germany					
COMP	COMP1	0.878 [0.851;0.900]	0.892 [0.872;0.909]	0.903 [0.885;0.918]	0.823 [0.796;0.846]
	COMP2	0.905 [0.886;0.921]			
	COMP3	0.937 [0.925;0.947]			
LIKE	LIKE1	0.930 [0.914;0.942]	0.913 [0.897;0.927]	0.915 [0.899;0.928]	0.852 [0.828;0.872]
	LIKE2	0.923 [0.905;0.937]			
	LIKE3	0.916 [0.901;0.930]			
SUSSAT	SUSSAT1	0.929 [0.914;0.941]	0.913 [0.893;0.928]	0.916 [0.897;0.929]	0.852 [0.824;0.875]
	SUSSAT2	0.914 [0.885;0.934]			
	SUSSAT3	0.926 [0.908;0.940]			

Values in brackets = 95% bias-corrected percentile bootstrap confidence interval (two-sided, 10,000 subsamples)

AVE average variance extracted, *COMP* perceived competence, *LIKE* perceived likeability, *SUSSAT* sustainable satisfaction

Table 4 HTMT criterion results for discriminant validity assessment

Reflective constructs	HTMT	
	China	Germany
LIKE <-> COMP	0.895 [$CI_{0.95}$: 0.948]	0.849 [$CI_{0.95}$: 0.877]
SUSSAT <-> COMP	0.885 [$CI_{0.95}$: 0.942]	0.853 [$CI_{0.95}$: 0.878]
SUSSAT <-> LIKE	0.943 [$CI_{0.95}$: 0.993]	0.917 [$CI_{0.95}$: 0.937]

$CI_{0.95}$ = 95th percentile of the bias-corrected percentile bootstrap confidence interval (based on 10,000 subsamples)

COMP perceived competence, *LIKE* perceived likeability, *SUSSAT* sustainable satisfaction

0.7 (Table 3). Next, we use the average variance extracted (AVE) to assess the reflective constructs' convergent validity. All the AVE values exceed the threshold of 0.5 (Table 3). We use the heterotrait-monotrait ratio of the correlations (HTMT, Henseler et al. 2015; Table 4) to determine the discriminant validity (i.e., by using the and absolute correlation values or HTMT+; Ringle et al. 2023). Since all the HTMT values are significantly below one (Franke and Sarstedt 2019), this allows us to establish the discriminant validity (Henseler et al. 2015). However, based on the more conservative HTMT assessment criteria (e.g., with a threshold value of 0.9), we could face discriminant validity issues in respect of LIKE and SUSSAT in both the Chinese and German samples even though we meet this criterion in all the other cases.

We conduct a redundancy analysis to assess our model's four formative antecedent constructs (i.e., QUAL, PERF, CSOR, and ATTR) of the two corporate reputation dimensions. Our analysis shows that the convergence validity of all four formatively measured constructs' has been established. The formative measurement model results show that the highest variance inflation factor (VIF) has a value of 4.824 for QUAL5 (Table 5). Consequently, all the VIF values are below the (more liberal) critical value of 5. Most of the other results are below the more conservative critical VIF value of 3 (Table 5). We therefore assume that the collinearity is not at a critical level. Moreover, the outer weights are significant and range between 0.201 and 0.357 in respect of China and between 0.181 and 0.333 in respect of Germany.

We begin the structural model analysis with an NCA (Dul 2016, 2020), which researchers can also carry out in a PLS-SEM context (Hair et al., 2024; Richter et al. 2020). We find that the effect sizes of the ceiling regression with

Table 5 Formative measurement model results

Constructs	Items	China			Germany		
		Outer weights	Significant ($p < 0.05$)	VIF	Outer weights	Significant ($p < 0.05$)	VIF
ATTR	ATTR1	0.357 [0.333;0.385]	Yes	1.472	0.333 [0.320;0.347]	Yes	2.663
	ATTR2	0.297 [0.274;0.319]	Yes	1.475	0.306 [0.296;0.319]	Yes	2.438
	ATTR3	0.344 [0.319;0.371]	Yes	1.406	0.320 [0.307;0.334]	Yes	2.619
	ATTR4	0.318 [0.289;0.345]	Yes	1.431	0.221 [0.201;0.238]	Yes	1.400
CSOR	CSOR1	0.230 [0.195;0.259]	Yes	1.327	0.218 [0.206;0.230]	Yes	2.361
	CSOR2	0.269 [0.248;0.291]	Yes	1.563	0.204 [0.193;0.213]	Yes	2.926
	CSOR3	0.292 [0.270;0.315]	Yes	1.745	0.238 [0.230;0.249]	Yes	4.114
	CSOR4	0.288 [0.267;0.310]	Yes	1.653	0.243 [0.234;0.254]	Yes	3.524
	CSOR5	0.280 [0.255;0.305]	Yes	1.533	0.237 [0.226;0.249]	Yes	3.167
PERF	PERF1	0.259 [0.229;0.288]	Yes	1.324	0.218 [0.209;0.228]	Yes	3.649
	PERF2	0.314 [0.286;0.343]	Yes	1.467	0.244 [0.235;0.255]	Yes	4.233
	PERF3	0.273 [0.245;0.301]	Yes	1.318	0.203 [0.192;0.213]	Yes	2.787
	PERF4	0.304 [0.280;0.330]	Yes	1.559	0.242 [0.233;0.254]	Yes	3.287
	PERF5	0.261 [0.222;0.294]	Yes	1.356	0.229 [0.216;0.241]	Yes	2.506
QUAL	QUAL1	0.205 [0.182;0.229]	Yes	1.581	0.192 [0.184;0.200]	Yes	2.766
	QUAL2	0.214 [0.196;0.235]	Yes	1.779	0.181 [0.173;0.188]	Yes	3.015
	QUAL4	0.201 [0.175;0.224]	Yes	1.506	0.193 [0.186;0.200]	Yes	3.543
	QUAL5	0.230 [0.210;0.251]	Yes	1.813	0.204 [0.197;0.212]	Yes	4.824
	QUAL6	0.247 [0.228;0.269]	Yes	1.765	0.186 [0.179;0.194]	Yes	2.977
	QUAL7	0.247 [0.225;0.271]	Yes	1.485	0.195 [0.188;0.204]	Yes	2.173

Values in brackets = 95% bias-corrected percentile bootstrap confidence interval (two-sided, 10,000 subsamples)

VIF variance inflation factor, *ATTR* perceived attractiveness, *CSOR* perceived corporate social responsibility, *PERF* perceived performance, *QUAL* perceived quality free disposal hull (CR-FDH) are above 0.1 and significant in all cases (Table 10, see Appendix), thereby confirming the structural model relationships' theoretically assumed necessity. Further, the structural model evaluation also shows that collinearity might have a slight effect on the estimated coefficients. The highest VIF has a value 4.772 (Table 6). However, all the other VIF values are close to three or even below. In the Chinese sample, one relationship is not significant (i.e., CSOR with COMP). This is also true of two German sample relationships (i.e., CSOR with COMP and PERF with LIKE). All the other coefficients in the structural model are significant (Table 6). However, the f^2 effect sizes (Table 7) are relatively low. In the Chinese sample, only the relationships between ATTR and LIKE, COMP and SUSSAT, and LIKE and SUSSAT have a moderate f^2 effect size of at least 0.15 in both samples (Table 6). While the structural model relationships explain 54.2% of the SUSSAT variance in the Chinese sample, they explain 74.6% of the SUSSAT in the German sample (see the R^2 results in Table 7). The model therefore provides pronounced and satisfyingly high R^2 values in respect of SUSSAT (i.e., the key target construct in the model). In addition, as pointed out for instance by Sarstedt et al. (2021), model fit assessment can also be relevant in a PLS-SEM context. Schuberth et al. (2023) highlight the role of model fit assessment in PLS-SEM in respect of criteria such as the GFI, NFI, and SRMR, or regarding bootstrap-based tests for model fit (see also Ringle et al. 2023). We apply the standardized root mean squared residual (SRMR) criterion in this research and consider a value of up to 0.08 as acceptable (Dash and Paul 2021). The SRMR results of 0.056 in respect of China and 0.053 for Germany are below 0.08, therefore supporting the estimated models' fit.

Looking at each country's structural model results (Figs. 2, 3, Table 6), we find that:

(1) QUAL is a driver of corporate reputation in both countries, especially of the customer-perceived corporate reputation's affective LIKE dimension;
(2) PERF is an important driver of COMP in both countries, whereas it is only slightly relevant for LIKE in

Table 6 Structural model relationships

Relationships	China				Germany			
	Direct effects	Significant ($p<0.05$)	f^2 effect size	VIF	Direct effects	Significant ($p<0.05$)	f^2 effect size	VIF
ATTR -> COMP	0.344 [0.257;0.423]	Yes	0.124	2.558	0.390 [0.303;0.472]	Yes	0.144	4.296
ATTR -> LIKE	0.411 [0.310;0.509]	Yes	0.161	2.558	0.449 [0.363;0.532]	Yes	0.199	4.296
COMP -> SUSSAT	0.350 [0.268;0.427]	Yes	0.152	1.751	0.315 [0.238;0.391]	Yes	0.157	2.480
CSOR -> COMP	0.068 [−0.028;0.162]	No	0.004	3.008	0.021 [−0.050;0.093]	No	0.001	3.196
CSOR -> LIKE	0.197 [0.090;0.298]	Yes	0.032	3.008	0.146 [0.064;0.230]	Yes	0.028	3.196
LIKE -> SUSSAT	0.458 [0.384;0.529]	Yes	0.261	1.751	0.598 [0.523;0.671]	Yes	0.568	2.480
PERF -> COMP	0.351 [0.264;0.435]	Yes	0.131	2.525	0.342 [0.250;0.423]	Yes	0.144	3.299
PERF -> LIKE	0.099 [0.007;0.186]	Yes	0.009	2.525	−0.022 [−0.108;0.063]	No	0.001	3.299
QUAL -> COMP	0.133 [0.059;0.210]	Yes	0.021	2.264	0.179 [0.087;0.272]	Yes	0.027	4.772
QUAL -> LIKE	0.154 [0.073;0.242]	Yes	0.026	2.264	0.351 [0.258;0.453]	Yes	0.109	4.772

Relationships	China		Germany	
	Indirect effects	Significant ($p<0.05$)	Indirect effects	Significant ($p<0.05$)
PERF -> COMP -> SUSSAT	0.123 [0.086;0.166]	Yes	0.108 [0.075;0.146]	Yes
CSOR -> COMP -> SUSSAT	0.024 [−0.009;0.059]	No	0.007 [−0.016;0.029]	No
ATTR -> LIKE -> SUSSAT	0.188 [0.133;0.250]	Yes	0.268 [0.212;0.327]	Yes
ATTR -> COMP -> SUSSAT	0.120 [0.082;0.165]	Yes	0.123 [0.087;0.163]	Yes
QUAL -> LIKE -> SUSSAT	0.070 [0.034;0.116]	Yes	0.210 [0.145;0.287]	Yes
CSOR -> LIKE -> SUSSAT	0.090 [0.043;0.139]	Yes	0.087 [0.039;0.136]	Yes
QUAL -> COMP -> SUSSAT	0.046 [0.020;0.078]	Yes	0.056 [0.026;0.095]	Yes
PERF -> LIKE -> SUSSAT	0.045 [0.004;0.088]	Yes	−0.013 [−0.066;0.037]	No

Values in brackets = 95% bias-corrected percentile bootstrap confidence interval (two-sided, 10,000 subsamples)

QUAL perceived quality, *PERF* perceived performance, *CSOR* perceived social responsibility, *ATTR* perceived attractiveness, *LIKE* perceived likeability, *COMP* perceived competence, *SUSSAT* sustainable satisfaction

Table 7 R^2 values and effect sizes

Explained variance	China			Germany		
	COMP	LIKE	SUSSAT	COMP	LIKE	SUSSAT
R^2	0.628	0.590	0.542	0.754	0.765	0.746
R^2_{adj}	0.626	0.587	0.540	0.752	0.763	0.746
Constructs	f^2 effect size for China			f^2 effect size for Germany		
	COMP	LIKE	SUSSAT	COMP	LIKE	SUSSAT
ATTR	0.124	0.161		0.144	0.199	
COMP			0.152			0.157
CSOR	0.004	0.032		0.001	0.028	
LIKE			0.261			0.568
PERF	0.131	0.009		0.144	0.001	
QUAL	0.021	0.026		0.027	0.109	

QUAL perceived quality, *PERF* perceived performance, *CSOR* perceived social responsibility, *ATTR* perceived attractiveness, *LIKE* perceived likeability, *COMP* perceived competence, *SUSSAT* sustainable satisfaction

China and does not show significant results in the German sample;

(3) CSOR is a driver of the affective corporate reputation dimension LIKE in both countries;

(4) ATTR is an important driver of both the reputation dimensions in both countries and is slightly more important for LIKE than for COMP.

In addition, we find that increased levels of corporate reputation dimensions (i.e., COMP and LIKE) lead to higher SUSSAT levels in both cultures (Table 6). Interestingly, LIKE is more important in Germany than in China, whereas COMP is more important in China than in Germany. In line with these results, ATTR has the strongest indirect effect via LIKE on SUSSAT in both China and Germany (Table 6). Additionally, in the Germany sample, QUAL also has a strong indirect effect via LIKE on SUSSAT. These country-specific outcomes reveal that the overall results are similar, but do not overlap completely. As an initial summary: the Chinese customer sample is more focused on the cognitive aspects and drivers, whereas the German customer sample tends to rate the affective dimensions higher.

Researchers use the $PLS_{predict}$ procedure to assess the model's predictive power further (Shmueli et al. 2016; Shmueli et al. 2019). In its original form, the $PLS_{predict}$ procedure uses early antecedent indicators to assess the predictive power. This, however, poses a particular challenge to models with mediators (Danks 2021). In our model, we focus on SUSSAT, the key target construct. The relationships between the early antecedent constructs ATTR, CSOR, PERF, and QUAL are fully mediated by the corporate reputation dimensions COMP and LIKE (Eberl 2010; Schwaiger 2004). Consequently, we revert to the new cross-validated predictive ability test (CVPAT; Liengaard et al. 2021), which uses a direct antecedent's approach to assess a predictive model and compare the models. Specifically, we apply the predictive CVPAT model assessment that Sharma et al. (2023) propose. Table 8 shows the CVPAT results in respect of tenfolds and ten repetitions. We find that both models have a predictive power regarding the indicator average benchmark. We support this finding regarding the more conservative linear model benchmark in respect of China; however, in terms of the SUSSAT in the German sample, we find a positive average loss difference regarding the linear model benchmark. Consequently, the PLS-SEM results cannot surpass this more restrictive benchmark to assess the model's predictive capabilities. In summary, we fully confirm the model's predictive power in respect of China, but only partially (i.e., for the indicator average benchmark, but not for the linear model benchmark) in respect of Germany. Note that a $PLS_{predict}$ cross-validation confirms this finding. While the results of SUSSAT's $Q^2_{predict}$ are above zero in both samples, we determine their predictive relevance for the linear model (LM) benchmark and for the sample from China, but not for the sample from Germany (Table 11). Whatever the case, our results support their sufficient predictive power in respect of China, while the results in respect of Germany only offer limited predictive power.

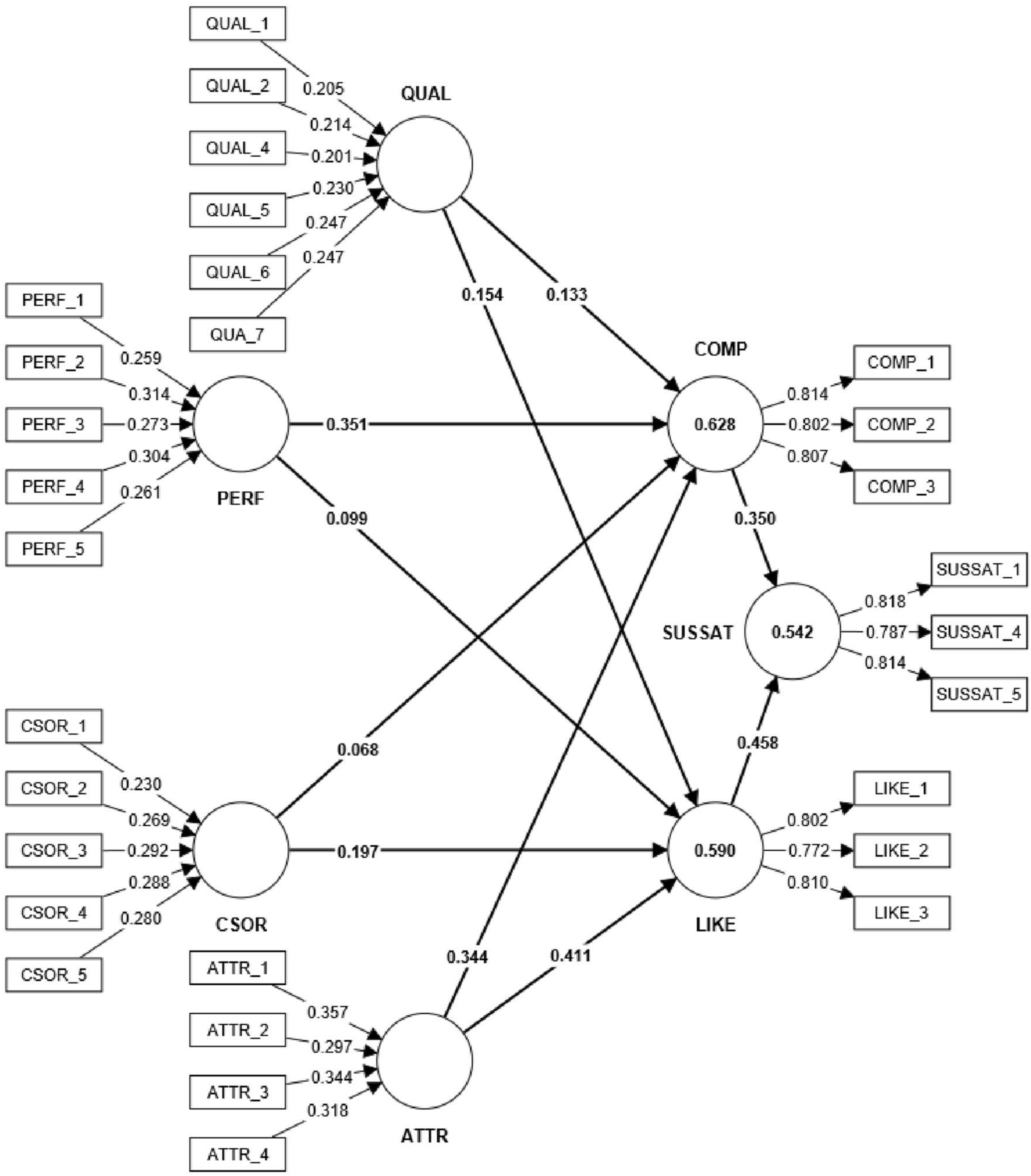

Fig. 2 PLS-SEM results in respect of China. *QUAL* perceived quality; *PERF* perceived performance; *CSOR* perceived corporate social responsibility; *ATTR* perceived attractiveness; *COMP* perceived competence; *LIKE* perceived likeability; *SUSSAT* sustainable satisfaction

We cannot undertake a PLS-SEM multigroup analysis of China and Germany, because we cannot determine the group's measurement model invariance (Hair et al. 2024). Consequently, we cannot test the differences in the path coefficients' statistical significance between these two groups. Nevertheless, we can qualitatively compare the differences in the country-specific path coefficients' magnitude. We do so using the IPMA (Hair et al., 2024; Ringle

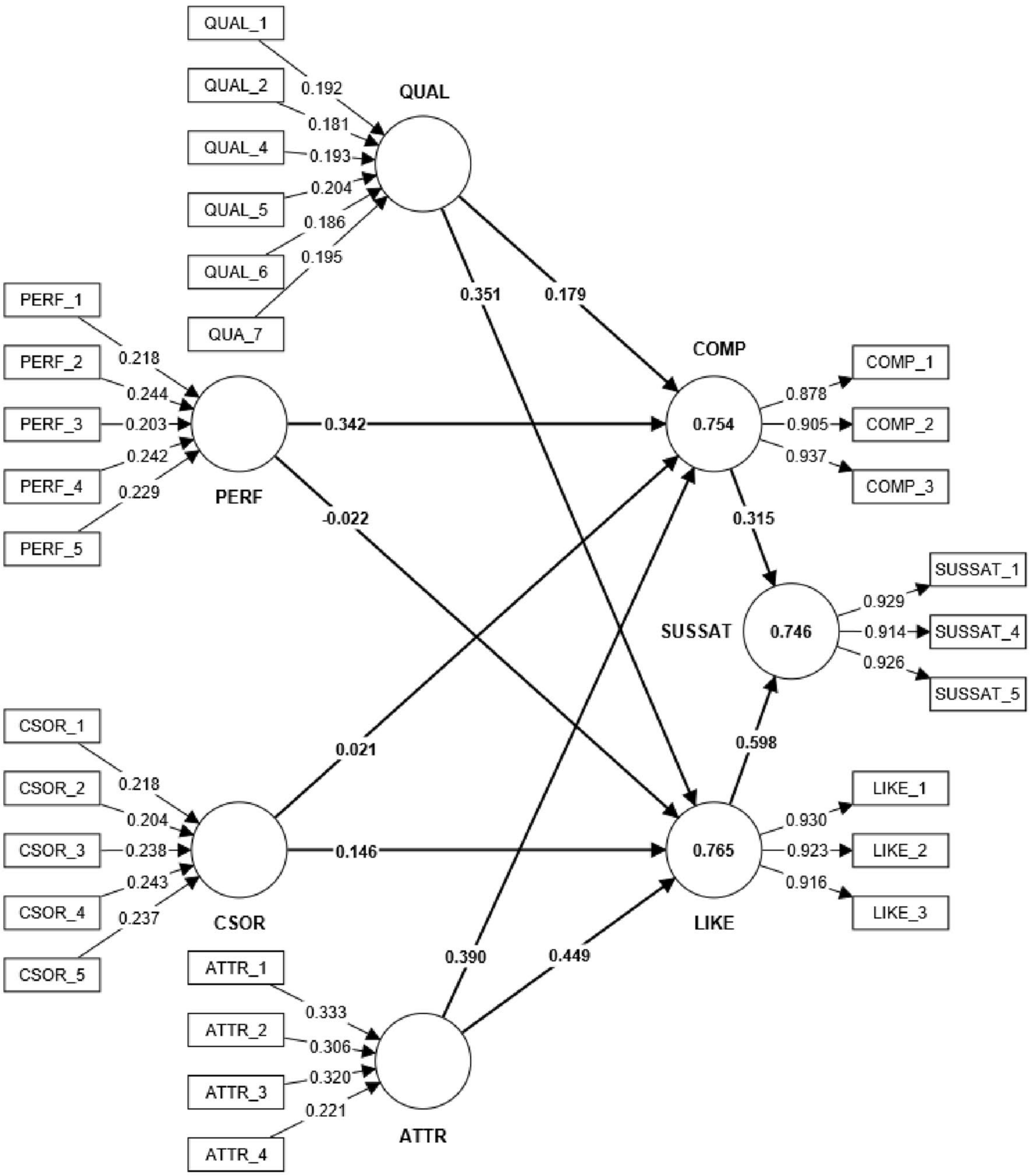

Fig. 3 PLS-SEM results in respect of Germany. *QUAL* perceived quality; *PERF* perceived performance; *CSOR* perceived corporate social responsibility; *ATTR* perceived attractiveness; *COMP* perceived competence; *LIKE* perceived likeability; *SUSSAT* sustainable satisfaction

and Sarstedt 2016), which has been applied in a variety of research contexts, including marketing (Liu et al. 2022). Figure 4 shows the IPMA results. The *x*-axis indicates the IPMA's overall effect on the key target construct, SUSSAT, which represents its importance. The *y*-axis represents performance expressed as the average unstandardized construct score rescaled from 0 (low performance) to 100 (high performance).

Table 8 CVPAT results

Constructs	China		Germany	
	Average loss difference	*p* value	Average loss difference	*p* value
Indicator average (IA) benchmark				
COMP	−0.540	0.000	−1.176	0.000
LIKE	−0.622	0.000	−1.670	0.000
SUSSAT	−0.461	0.000	−1.520	0.000
Overall	−0.541	0.000	−1.455	0.000
Linear model (LM) benchmark				
COMP	−0.008	0.471	0.017	0.200
LIKE	0.007	0.680	−0.020	0.097
SUSSAT	−0.001	0.938	0.077	0.001
Overall	−0.001	0.939	0.025	0.015

LIKE perceived likeability, *COMP* perceived competence, *SUSSAT* sustainable satisfaction

The IPMA results in Fig. 4 clearly show that, in respect of China, all of the constructs that affect SUSSAT show a higher performance. In respect of this country, the LIKE construct is clearly of the greatest importance for SUSSAT, followed by COMP and ATTR. The other constructs are of less importance. LIKE also has the greatest importance in the German sample, but this construct is followed by ATTR, COMP, and QUAL. While there is a large overlap in both countries' set of important constructs, LIKE is of far greater importance in Germany, while the QUAL construct clearly has additional relevance. In general, the IPMA results indicate that managers in both countries should focus on improving the LIKE construct, as it has greater importance with regard to increasing the SUSSAT levels. The second highest priority should be improving the ATTR and the COMP in both countries. QUAL only has the third highest priority in Germany.

Discussion

Our results show that, with two exceptions, we can confirm most of our hypotheses. The first exception is that higher levels of CSOR do not lead to higher levels in customer-perceived reputation's (H3a) cognitive dimension in either China or Germany. One of the reasons for this result could be that commercial bank customers do not truly value CSR measures. A customer segment that does value this measure highly would rather choose another bank type, such as cooperative banks (Damberg et al. 2022). We could not confirm hypothesis H4b either, i.e., that, according to the German dataset, higher levels of ATTR do not lead to higher levels of customer-perceived reputation's affective dimension. Germany's low-context culture might explain this result. The outer appearance that leads to ATTR is not as relevant for LIKE, while a factor, such as the quality (of the relationship) with the bank, is. Two decades ago, Wang et al. (2003) already found that PERF was the most important driver of corporate reputation in China, especially in respect of COMP. With reference to Hall's context theory (Hall 1976; Hall and Hall 1990), which argues that people from different

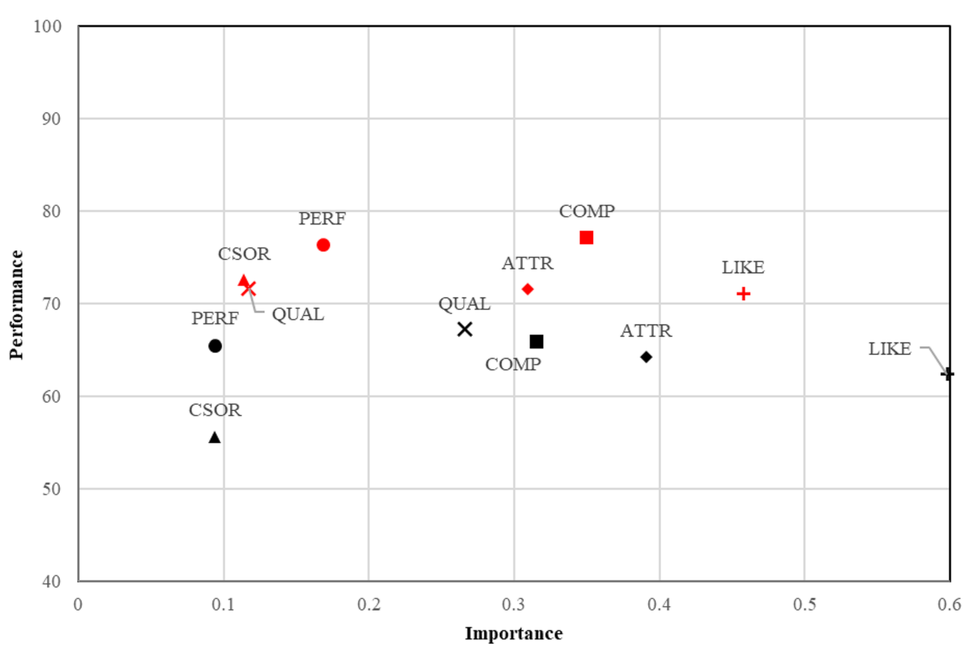

Fig. 4 Importance-performance map analysis results (standardized). *Red color* China; *black* Germany. *QUAL* perceived quality; *PERF* perceived performance; *CSOR* perceived corporate social responsibility; *ATTR* perceived attractiveness; *COMP* perceived competence; *LIKE* perceived likeability; *SUSSAT* sustainable satisfaction. (Color figure online)

cultures might react differently to complex messages (Kim et al. 1998), we argue that these initial results revealed that people in high-context cultures rely on pre-established information, including unwritten traditional habits, self-evident values, and universally recognized behavior patterns in their society. Low-context cultures, on the other hand, emphasize rationality and logic, i.e., drawing logical conclusions based on rational practices and conveying precise information through clear language. In these cultures, people tend to include most of the information directly and try—as far as possible—to express their meaning fully through (textual) information. These cultures rarely hide information in the transmission process.

Interestingly, CSOR was not confirmed as a significant driver of bank reputation in either of the two countries. Regarding the reputation dimensions, LIKE is more important for building SUSSAT in Germany than in China. In addition, we found that QUAL is important for LIKE, but only for the sample of German commercial bank customers. This might be explained by taking commercial banks in China's state-owned nature into account. The homogenization of the banking segment has made it difficult for banking institutions to provide the quality of services required to retain consumers (Agarwal et al. 2010).

As mentioned above, Chinese bank customers value the cognitive aspects and drivers more, whereas German bank customers rate affective aspects higher. In terms of the indirect effect results, we could also see a difference between the Chinese and German subsamples, in that the indirect effect of perceived performance, perceived likeability, and sustainable customer satisfaction is significant for the Chinese subsample, but not the German one. This finding points to Chinese customers being more interested in performance-related aspects than in, for example, their relationship with the bank, which relates back to the cultural differences between low and high context societies.

Our model and its empirical results have implications from a theoretical, practical, and methodological perspective. From a theoretical perspective, we offer a simplified, but robust, model for future research to investigate the specific cultural similarities and differences in customer perceptions in low-context (China) and high-context (Germany) cultures. Scholars in the field of bank marketing could apply and extend our robust model further. The identified similarities and differences offer practitioners (i.e., marketing managers of internationally operating banks) insights, because we offer empirical evidence of their decision making in terms of building customer relationships in two different cultural settings. For example, Deutsche Bank operates in both cultures and might therefore need to adopt different communication strategies in terms of corporate reputation to ensure long-term customer satisfaction in each country.

These implications are part of the strategic decisions banks need to consider in a highly competitive international market, because (long-term) customer satisfaction is linked to the firm performance (Otto et al. 2020). To be more precise, in respect of bank managers and board members, this study's findings emphasize that LIKE is the most important aspect driving the SUSSAT of bank customers, which is, in turn, strongly driven by ATTR. Bank managers could address this by designing their stores, internet presence, and logos in line with customer preferences, thereby using a holistic approach to enhance the bank's corporate reputation (Balmer 1998).

From a methodological perspective, we validate the relationships in our model by using one target construct (i.e., SUSSAT) instead of two (i.e., satisfaction and loyalty, on which prior research normally focused), and confirm our developed model's explanatory and predictive power in two culturally diverse settings.

Conclusions and future research

Customer satisfaction and loyalty are a central research object in marketing since companies' success is rooted in these key elements (Fornell et al. 2006). The American Customer Satisfaction Index (ACSI) is one of the most important models to explain customer satisfaction and loyalty, as well as support analyses across different industries (Fornell et al. 1996, 2020). In addition, the related European customer satisfaction index (ECSI) model encourages comparisons of customer satisfaction's and loyalty's drivers of industries across countries (Cassel and Eklöf 2001; Eklöf and Westlund 2002; Johnson et al. 2002). Schwaiger's (2004) corporate reputation model does not generally explain customer satisfaction and loyalty; instead, it focuses exclusively on corporate reputation's relevance through its core dimensions COMP and LIKE, as well as on their central drivers to explain customer satisfaction and loyalty. Similar to the ACSI and ECSI models, the corporate reputation model's analysis and comparison across different industries and countries are also valuable and important research areas with high practical relevance (e.g., Carreras-Romero et al. 2019; Swoboda et al. 2016, 2017). With this study, we answer Damberg et al.'s (2022) research call to undertake future research and to not only make cross-country comparisons, but to also verify a robust research model that would further validate SUSSAT as a theoretically and methodologically useful measure for assessing long-term bank customer satisfaction. With this study, we verify a well-established reputation-satisfaction model with a long-term focus on the Chinese and German commercial banking sectors, which will ensure robust results.

Our study not only contributes to strategic bank marketing research, but also offers bank managers valuable support. On the one hand, we show ATTR is a specifically important driver of bank reputation in both China and Germany. On the other hand, we also confirm that, in both countries, the affective reputation dimension is more important for SUSSAT. Moreover, we apply the IPMA from a more practical perspective. The results indicate that bank managers might prioritize LIKE to enhance the SUSSAT construct. To improve LIKE's performance, bank managers should thereafter prioritize ATTR. In contrast, COMP improvements depend particularly strongly on the COMP construct. Managers should therefore give the highest priority to focusing on ATTR and COMP's performance improvements.

This research focuses on identifying the key drivers of customer-based reputation and SUSSAT in two culturally different countries. From a marketing perspective (Kemper et al. 2011), the cultural differences between China and Germany impact the perception of reputation and customer satisfaction (Zhang and Schwaiger 2009). This is also true of the banking sector. Understanding the differences in corporate reputation's relevance for SUSSAT could be useful for banks operating in both these countries or planning to expand internationally. Consequently, understanding and comparing corporate reputation's relevance in a country-specific context could help bank managers formulate effective strategies (Dolphin 2004) in order to maintain customer satisfaction and build a positive reputation in different markets. Our study confirms the extended corporate reputation model's relevance for both cultures. The results also suggest that there is a large overlap in the set of important constructs and identify ATTR as the most important driver of customer-perceived bank reputation. We also reveal the differences between the two countries in respect of certain constructs' relative importance, such as that of LIKE and QUAL. Our confirmation of the extended corporate reputation model's general applicability in culturally different countries and our insights into country-specific effects could be useful for banks in both countries when designing their marketing campaigns and communication strategies to target customers effectively.

Referring to Hall's context theory once again, we understand that different cultures have different contextual characteristics. There are many significant differences between Western (e.g., Germany) and Eastern (e.g., Chinese) cultures. The variety of influencing cultural aspects, such as a country's history, geography, customs, and values, all of which are covered in high- and low-context cultures, could, for example, explain these significant differences. According to Hall, the difference between low- and high-context cultures lies in their different ways of disseminating information. In low-context cultures, information dissemination is less dependent on the context and, instead, incorporated in a clear and concise language/communication. By adapting communication strategies that fit each cultural setting, commercial banks with a low degree of differentiation products could target specific consumer groups in their specific countries/cultures.

Future research could distinguish between the two countries' informal and formal institutional environments (see Schlägel and Sarstedt 2016). Furthermore, future research could relate to signaling theory and emphasize the signal fit's importance. In this context, signal fit would mean that the signals a bank sends match the reputation it endeavors to develop. Given the different cultural contexts in which the study was conducted, there might also be differences in the effects that the two corporate reputation dimensions have on SUSSAT, the target construct. Such future research results could be possible, because they show whether banks need to prioritize increasing their perceived competence or their perceived likability in order to improve their SUSSAT, which depends on the cultural context. Given the relationships between the four antecedents and corporate reputation's two dimensions, suggestions could subsequently be developed regarding how banks could ensure the signal fit in each of the two countries. Finally, future research could apply the SUSSAT model in other cultural settings. Marketing researchers could also gain additional insights by comparing different industries, which the ACSI model data could provide (Fornell et al. 1996, 2020). Finally, future research could extend the model to include additional important target variables (e.g., bank performance).

Appendix

See Tables 9, 10, 11.

Table 9 Demographics

Sample criteria	China (*n*)	China (%)	Germany (*n*)	Germany (%)
Gender				
Male	302	41.1	301	48.2
Female	432	58.9	322	51.6
Diverse	0	0	1	0.2
Age				
18–24	137	18.7	18	2.9
24–34	336	45.7	70	11.2
35–44	188	25.6	97	15.5
45–54	58	7.9	136	21.8
55–65	13	1.8	182	29.2
> 65	2	0.3	121	19.4
Living status				
Preferred not to answer	0	0.0	4	0.6
Living alone	176	24.0	145	23.2
Living with a partner	41	5.6	89	14.3
Registered civil partnership	0	0.0	3	0.5
Married	497	67.7	283	45.4
Divorced	15	2.0	75	12.0
Widowed	5	0.7	25	4.0
Education (highest level)				
Preferred not to answer	0	0.0	0	0.0
No education	0	0.0	1	0.2
"Hauptschule" (finished 9th grade)	60	8.2	34	5.5
"Mittlere Reife" (finished 10th grade)	0	0.0	126	20.1
"Fachhochschulreife" (finished 12th grade)	67	9.1	28	4.5
Abitur (high school diploma)	0	0.0	77	12.3
Ausbildung	0	0.0	180	28.9
University degree	607	82.7	178	28.5
Occupational status				
Preferred not to answer	0	0.0	8	1.3
Unemployed	16	2.0	25	4.0
Retired	6	1.0	190	30.5
Houseman/housewife	29	4.0	23	3.7
In education	8	1.0	6	0.9
Student studying at a university	68	9.3	13	2.1
Self-employed	62	8.4	42	6.7
Employed	545	74.3	317	50.8
Monthly household income (after taxes)				
Preferred not to answer	0	0.0	62	10.0
< 750EUR/1000CNY	59	8.0	32	5.1
750–1250/EUR1000–2000CNY	53	7.2	92	14.7
1250–2000/EUR2000–3000CNY	55	7.5	155	24.8
2000–3500/EUR3000–5000CNY	162	22.1	167	26.8
3500–5000/EUR5000–10,000CNY	265	36.1	85	13.6
> 5000EUR/10,000CNY	140	19.1	31	5.0

Table 10 Necessary condition analysis results of the CR-FDH ceiling line

Independent constructs	China			Germany		
	SUSAT*	CI	*p* value	SUSAT*	CI	*p* value
COMP	0.298	0.11	0.000	0.197	0.016	0.000
LIKE	0.134	0.07	0.000	0.133	0	0.000
Independent constructs	China			Germany		
	COMP*	CI	*p* value	COMP*	CI	*p* value
ATTR	0.191	0.122	0.000	0.237	0.032	0.000
CSOR	0.213	0.083	0.000	0.109	0.019	0.000
PERF	0.329	0.109	0.000	0.233	0.04	0.000
QUAL	0.158	0.055	0.000	0.244	0.035	0.000
Independent constructs	China			Germany		
	LIKE*	CI	*p* value	LIKE*	CI	*p* value
ATTR	0.227	0.126	0.000	0.295	0.032	0.000
CSOR	0.178	0.108	0.000	0.108	0.019	0.000
PERF	0.250	0.139	0.000	0.212	0.043	0.000
QUAL	0.163	0.076	0.000	0.328	0.035	0.000

CI 95% permutation confidence interval (one-sided, 10,000 permutations), *QUAL* perceived quality, *PERF* perceived performance, *CSOR* perceived social responsibility, *ATTR* perceived attractiveness, *COMP* perceived competence, *LIKE* perceived likeability, *SUSSAT* sustainable satisfaction

*Dependent construct

Table 11 $PLS_{predict}$ results of the target construct (SUSSAT)

Indicator	$Q^2_{predict}$	$RMSE_{PLS}$	$RMSE_{LM}$	$RMSE_{PLS} - RMSE_{LM}$
China				
SUSSAT1	0.415	0.868	0.839	0.029
SUSSAT2	0.278	0.980	0.992	−0.012
SUSSAT3	0.313	1.024	1.039	−0.015
Germany				
SUSSAT1	0.652	0.865	0.785	0.080
SUSSAT2	0.565	0.936	0.892	0.044
SUSSAT3	0.668	1.001	0.991	0.010

RMSE root-mean square error, *LM* linear model, *SUSSAT* sustainable satisfaction

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