The Effects of General and Mobile Online Shopping Skilfulness and Multichannel Self-Efficacy on Consumer Showrooming Behaviour

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Abstract Although showrooming behaviour is a characteristic aspect of modern omnichannel retailing, our understanding of its antecedents remains limited. In this study, we aim to address this gap in prior research by examining how showrooming behaviour is affected by three different kinds of perceived consumer capabilities: general online shopping skilfulness, mobile online shopping skilfulness, and multichannel self-efficacy. The examination is done by utilising data from 1,024 Finnish consumers, which was collected with an online survey in 2021 and is analysed with structural equation modelling (SEM). In summary, we find mobile online shopping skilfulness to have a strong positive effect on showrooming behaviour, the total effect of general online shopping skilfulness to be statistically not significant, and the effect of multichannel self-efficacy to be negative. In addition, we find several interesting gender and age differences. We conclude the paper with a detailed discussion of the findings from both theoretical and practical perspectives.

Keywords: general online shopping skilfulness, mobile online shopping skilfulness, multichannel self-efficacy, showrooming behaviour, gender and age differences.

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1 Introduction

During the past decade, we have witnessed the emergence of so-called omnichannel retailing, which refers to the integration of multiple retail channels and other touchpoints between retailers, brands, and consumers in order to provide consumers with a single seamless and consistent customer experience (Rigby, 2011; Brynjolfsson et al., 2013; Verhoef et al., 2015; Akter et al., 2021). One characteristic aspect of this novel type of retailing is so-called showrooming behaviour, which is defined by Rapp et al. (2015) as "a practice whereby consumers visit a brick-and-mortar retail store to (1) evaluate products or services first-hand and (2) use mobile technology while in-store to compare products for potential purchase via any number of channels". Currently, this practice is very common. For example, in a recent study by Shopify (2021), 53% of the surveyed consumers said that they are likely to practise showrooming over the next year. However, in spite of its commonness and some prior studies on it (Sahu et al., 2021), our understanding of the antecedents of showrooming behaviour remains limited (Daunt & Harris, 2017), making it difficult for retailers to control and manage showrooming behaviour in order to maximise its potential advantages, such as better customer experience, and minimise its potential disadvantages, such as losses in sales (Schneider & Zielke, 2020). More specifically, there seems to exist a clear gap in our understanding of how various consumer capabilities, or consumer beliefs about and perceptions of these capabilities, affect their showrooming behaviour (Sahu et al., 2021). In this study, we aim to address this gap in prior research by examining how showrooming behaviour is affected by three different kinds of perceived consumer capabilities: general online shopping skilfulness, mobile online shopping skilfulness, and multichannel self-efficacy. In addition, as several prior studies have suggested showrooming behaviour to be affected by demographic variables like gender and age (Dahana et al., 2018; Burns et al., 2019; Sahu et al., 2021), we also examine the potential gender and age differences in the effects of these perceived consumer capabilities on showrooming behaviour as well as in the perceived consumer capabilities and showrooming behaviour themselves. This all is done by utilising data from 1,024 Finnish consumers, which was collected with an online survey in 2021 and is analysed with structural equation modelling (SEM).

After this introductory section, we briefly present our research model in Section 2. The methodology and results of the paper are reported in Sections 3 and 4, and the results are discussed in more detail in Section 5. Finally, the paper concludes with a brief discussion of the limitations of the present study and some potential paths for future research in Section 6.

2 Research Model

In our research model, which is illustrated in Figure 1, we hypothesise showrooming behaviour to be positively affected by three different kinds of perceived consumer capabilities: general online shopping skilfulness, mobile online shopping skilfulness, and multichannel self-efficacy. Of these, general online shopping skilfulness refers to the general online shopping skills of consumers, such as their ability to search for information and place orders over the Internet, whereas mobile online shopping skilfulness refers to the online shopping skills of consumers concerning transactions that are completed specifically by using smartphones. In turn, multichannel self-efficacy is defined by Chiu et al. (2011) as "the ability and confidence of consumers to employ multiple channels, including online and brick-and-mortar stores, to finish a transaction, starting with information search and ending in purchase".

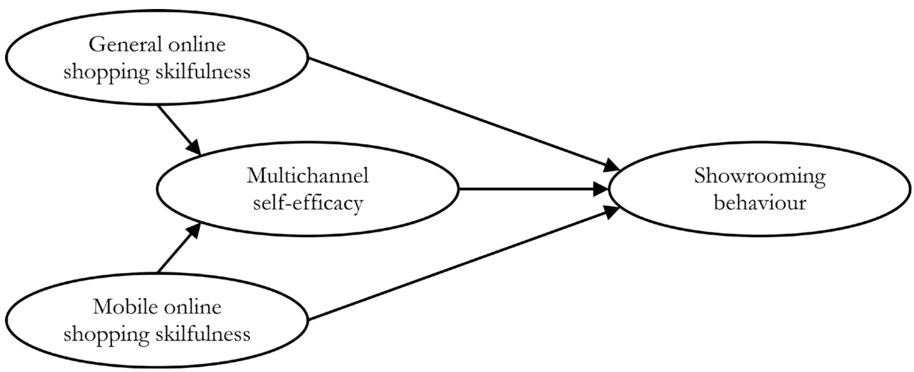

Figure 1: Research model

Of these perceived consumer capabilities, general online shopping skilfulness obviously acts as a critical prerequisite for showrooming behaviour. Without it, consumers would not be able to utilise online channels for information search and ordering, but their choice of channels would be limited to offline channels only.

However, in addition to general online shopping skilfulness, showrooming behaviour requires consumers to possess more specific mobile online shopping skilfulness in order for them to be able to search for information and potentially place orders while in-store by using their smartphones. Moreover, we argue that in addition to general and mobile online shopping skilfulness, showrooming behaviour requires consumers to possess more comprehensive multichannel self-efficacy in order for them to have confidence in their capabilities to use not only one but multiple channels during the purchasing process, such as when first physically examining the product at a brick-and-mortar store and then searching for more information about it and potentially ordering it from an online store. This argument also gains support from a prior study by Arora et al. (2017), who found multichannel self-efficacy to positively affect showrooming intention, albeit not directly but indirectly via perceived behavioural control. Finally, in our research model, we also hypothesise general and mobile online shopping skilfulness to have positive effects on multichannel self-efficacy because the more skilful consumers are in using online channels, the more confidence they are also likely to have in their capabilities of using these channels in addition to offline channels during the purchasing process.

3 Methodology

The data for testing the research model was collected from Finnish consumers in 2021 with an online survey, in which the model constructs were measured reflectively by three items each. The items measuring general online shopping skilfulness (GOSS) were adapted from the Internet shopping skill scale by Rose et al. (2012), whereas the items measuring mobile online shopping skilfulness (MOSS) were adapted from the mobile skilfulness scale by Lu and Su (2009). In turn, the items measuring multichannel self-efficacy (MCSE) were adapted from the study by Chiu et al. (2011), whereas the items measuring showrooming behaviour (SRB) were adapted from the study by Li et al. (2018). The wordings of these items (before the translation from English to Finnish) are reported in Appendix A. The measurement scale was a standard seven-point Likert scale (1 = strongly disagree … 7 = strongly agree). The respondents also had the option not to respond to a specific item, which resulted in a missing value.

The collected data was analysed with covariance-based structural equation modelling (CB-SEM) by using the Mplus version 8.8 software (Muthén & Muthén, 2022) and following the guidelines by Gefen et al. (2011) for SEM in administrative and social science research. As the model estimator, we used the MLR option of Mplus, which stands for maximum likelihood estimator robust to non-normal data. The potential missing values were handled by using the FIML option of Mplus, which stands for full information maximum likelihood and uses all the available data in model estimation. The potential gender and age differences were examined with multiple group analysis (MGA) by following the testing procedure proposed by Steenkamp and Baumgartner (1998) for establishing measurement invariance. In it, increasingly strict constraints on parameter equality are added across the groups and the fit of the resulting constrained model is compared to the fit of the unconstrained model. If the constraints result in no statistically significant deterioration in model fit, then the hypothesis on the specific type of measurement invariance is supported. Configural invariance is tested by estimating the model separately in each group while constraining only the simple model structure as equal across the groups, whereas metric and scalar invariance are tested by additionally constraining the indicator loadings and indicator intercepts as equal across the groups. After this, the differences in the model constructs can be tested by examining their estimated mean scores in each group. Of the groups, one is typically specified as a reference group, in which the construct mean scores are fixed to zero and against which the construct mean scores of the other groups are compared. In addition, the differences in the effects between the model constructs can be tested by constraining the estimated effect sizes as equal across the groups. As a statistical test for examining the potential deteriorations in model fit, we used the χ^2 test of difference, in which the value of the test statistic was corrected with the Satorra-Bentler (2001) scaling correction factor (SCF) due to the use of MLR as the model estimator. However, because the χ^2 test of difference is known to suffer from a similar sensitivity to sample size as the χ^2 test of model fit, we also considered the potential changes in the model fit indices, as suggested by Steenkamp and Baumgartner (1998).

4 Results

In total, we received 1,028 responses to our online survey, of which four responses had to be dropped due to missing data. Thus, the sample size of this study was 1,024 responses. The descriptive statistics of this sample in terms of the gender, age, and income distributions of the respondents as well as the reference gender, age, and income distributions of the Finnish population (Statistics Finland, 2022; Finnish Tax Administration, 2022) are reported in Table 1, showing that the sample had good representativeness. In the following three subsections, we first assess the reliability and validity of the estimated model at both indicator and construct levels, then report the model fit and model estimates, and finally examine the potential gender and age differences.

Table 1: Sample statistics and the reference statistics of the Finnish population

	Sample (N)	Sample (%)	Finland (%)
Gender			
Man	497	48.5	50.3
Woman	527	51.5	49.7
Age			
18–29 years	188	18.4	19.3
30–39 years	213	20.8	18.1
40–49 years	194	18.9	16.9
50–59 years	197	19.2	17.6
60–75 years	232	22.7	28.1
Personal taxable income			
Under 20,000 €	304	34.3	39.4
20,000–39,999 €	349	39.3	35.7
40,000 € or over	234	26.4	25.0
Missing	137	–	–

4.1 Model Reliability and Validity

Construct reliabilities were assessed by using the composite reliabilities (CR) of the constructs (Fornell & Larcker, 1981), which are commonly expected to be greater than or equal to 0.7 (Nunally & Bernstein, 1994). The CR of each construct is reported in the first column of Table 2, showing that all the constructs met this criterion. In turn, construct validities were assessed by examining the convergent and discriminant validities of the constructs by using the two criteria proposed by Fornell and Larcker (1981). They are both based on the average variance extracted (AVE) of the constructs, which refers to the average proportion of variance that a construct explains in its indicators. In order to have acceptable convergent validity, the first criterion expects each construct to have an AVE of at least 0.5. This means that, on average, each construct should explain at least half of the variance in its indicators. The AVE of each construct is reported in the second column of Table 2, showing that all the constructs met this criterion. In order to have acceptable discriminant validity, the second criterion expects each construct to have a square root of AVE greater than or equal to its absolute correlations with the other model constructs. This means that, on average, each construct should share at least an equal proportion of variance with its indicators than it shares with these other model constructs. The square root of AVE of each construct (on-diagonal) and the correlations between the constructs (off-diagonal) are reported in the remaining columns of Table 2, showing that this criterion was also met by all the constructs.

Table 2: Construct statistics (* = p < 0.001)**

Construct	CR	AVE	GOSS	MOSS	MCSE	SRB
GOSS	0.915	0.783	0.885			
MOSS	0.941	0.842	0.617***	0.917		
MCSE	0.910	0.772	0.837***	0.639***	0.879	
SRB	0.863	0.679	0.462***	0.774***	0.414***	0.824

Finally, indicator reliabilities and validities were assessed by using the standardised loadings of the indicators, which are reported in Table 3 together with the means and standard deviations (SD) of the indicator scores as well as the percentages of missing values. In the typical case of each indicator loading on only one construct, the standardised loading of each indicator is commonly expected to be statistically significant and greater than or equal to 0.707 (Fornell & Larcker, 1981). This is equivalent to the standardised residual of each indicator being less than or equal to 0.5, meaning that at least half of the variance in each indicator is explained by the construct on which it loads. The only indicator that did not quite meet this criterion was SRB3, but we decided not to drop it from the model because it was not found to compromise the overall reliability or validity of the SRB construct (cf. Table 2).

Table 3: Indicator statistics (* = p < 0.001)**

Indicator	Mean	SD	Missing	Loading
GOSS1	5.775	1.308	0.0%	0.887***
GOSS2	5.470	1.429	0.5%	0.899***
GOSS3	5.664	1.296	0.3%	0.868***
MOSS1	5.284	1.754	0.1%	0.921***
MOSS2	5.175	1.760	0.4%	0.907***
MOSS3	5.355	1.743	0.3%	0.924***
MCSE1	5.977	1.166	0.1%	0.870***
MCSE2	5.772	1.299	0.0%	0.892***
MCSE3	5.783	1.253	0.4%	0.874***
SRB1	4.933	1.871	0.1%	0.871***
SRB2	4.997	1.847	0.2%	0.892***
SRB3	4.147	1.992	0.7%	0.695***

4.2 Model Fit and Model Estimates

The results of model estimation in terms of the standardised effect sizes and their statistical significance, the proportions of explained variance (R^2), as well as model fit are reported in Figure 2. Model fit was assessed by using the χ^2 test of model fit and four model fit indices recommended in recent methodological literature (Hu & Bentler, 1999): the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardised root mean square residual (SRMR). Of them, the χ^2 test of model fit rejected the null hypothesis of the model fitting the data, which is common in the case of large samples (Bentler & Bonett, 1980). In contrast, the values of the four model fit indices all clearly met the cut-off criteria recommended by Hu and Bentler (1999): CFI $\geq$ 0.95, TLI $\geq$ 0.95, RMSEA $\leq$ 0.06, and SRMR $\leq$ 0.08. Thus, we consider the overall fit of the model acceptable. We also found no serious signs of multicollinearity or common method bias. The variance inflation factor (VIF) scores calculated from the factor scores were all clearly less than ten (Hair et al., 2018), and the Harman's single factor test (Podsakoff et al., 2003) suggested a very bad model fit ($\chi^2(54)$ = 5,695.861, $p < 0.001$, CFI = 0.067, TLI = 0.000, RMSEA = 0.319, SRMR = 0.124).

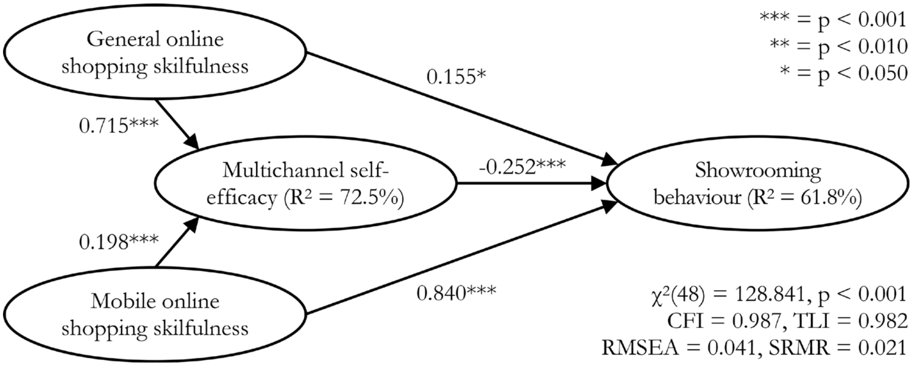

Figure 2: Model estimates and model fit

Of the perceived consumer capabilities, both GOSS and MOSS were found to have statistically significant and positive effects on MCSE, with GOSS having a stronger effect than MOSS, whereas MCSE together with GOSS and MOSS were found to have statistically significant effects on SRB, with MOSS having a strong positive effect, GOSS having a weak positive effect, and MCSE having a negative effect. However, when also considering the indirect effects of GOSS and MOSS on SRB via MCSE, the total effect of GOSS on SRB was found to be statistically not significant (-0.025), whereas the total effect of MOSS on SRB remained statistically significant and positive (0.790***). In total, the model explained 72.5% of the variance in MCSE and 61.8% of the variance in SRB.

4.3 Gender and Age Differences

In order to examine the potential gender and age differences, the sample was first split into four groups to be compared against each other: men aged under 50 years (N = 258), women aged under 50 years (N = 337), men aged 50 years or over (N = 239), and women aged 50 years or over (N = 190). The threshold for the age split was determined on an empirical basis, as it resulted in the evenest split and there was also a distinct drop in the scores of many measurement items at around 50 years of age. After this, measurement invariance across the groups was tested. The results of these tests are reported in Table 4. As can be seen, the tests supported the hypothesis on both configural and full metric invariance but only partial scalar invariance. The intercepts that were not found to be invariant across the groups were those of SRB3 among men aged under 50 years and women aged under 50 years, SRB2 among women aged 50 years or over, and GOSS3 among men aged 50 years or over. However, this partial scalar invariance can only be considered to compromise the mean score comparisons concerning the SRB construct between men aged under 50 years and women aged 50 years or over as well as between women aged under 50 years and women aged 50 years or over. In those cases, the SRB construct is measured by only one indicator that has both an invariant loading and an invariant intercept across the compared groups (cf. Steenkamp & Baumgartner, 1998).

Table 4: Measurement invariance tests (1 = men aged under 50 years, 2 = women aged under 50 years, 3 = men aged 50 years or over, 4 = women aged 50 years or over)

Invariance	χ^2	df	SCF	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	p
Configural	346.427	192	1.3179	0.975	0.965	0.056	0.033	–	–	–
Full metric	382.747	216	1.3019	0.973	0.966	0.055	0.050	35.559	24	0.061
Full scalar	473.526	240	1.2693	0.961	0.958	0.062	0.057	105.286	24	< 0.001
Partial scalar (SRB3 in 1)	445.949	239	1.2702	0.966	0.962	0.058	0.056	70.073	23	< 0.001
Partial scalar (SRB3 in 2)	429.931	238	1.2713	0.968	0.965	0.056	0.055	49.722	22	0.001
Partial scalar (SRB2 in 4)	421.329	237	1.2724	0.970	0.966	0.055	0.055	39.011	21	0.010
Partial scalar (GOSS3 in 3)	414.507	236	1.2728	0.971	0.967	0.054	0.053	30.554	20	0.061
Full path	422.891	251	1.2881	0.972	0.970	0.052	0.060	11.212	15	0.737

The results of the construct mean score comparisons across the groups are reported in a tabular form in Table 5 and a graphical form in Figure 3. In terms of gender, women were found to have higher mean scores than men in MOSS, MCSE, and SRB among those aged under 50 years but higher mean scores in GOSS among those aged 50 years or over. In turn, in terms of age, those aged 50 years or over were found to have lower mean scores in all the four constructs in comparison to those aged under 50 years, of which the difference in GOSS was more pronounced among men than women, whereas the difference in SRB was more pronounced among women than men. Finally, the last row in Table 4 reports the result of the full path invariance test, which suggested that, overall, there were no statistically significant differences across the groups in the effects between the model constructs.

Table 5: Construct mean scores (1 = men aged under 50 years, 2 = women aged under 50 years, 3 = men aged 50 years or over, 4 = women aged 50 years or over)

	2 vs. 1	3 vs. 1	4 vs. 1	3 vs. 2	4 vs. 2	4 vs. 3
GOSS	0.085	-0.610***	-0.283*	-0.695***	-0.368**	0.327*
MOSS	0.271**	-1.016***	-0.700***	-1.287***	-0.971***	0.316
MCSE	0.204**	-0.208*	-0.051	-0.413***	-0.256*	0.157
SRB	0.402***	-0.938***	-0.957***	-1.341***	-1.360***	-0.019

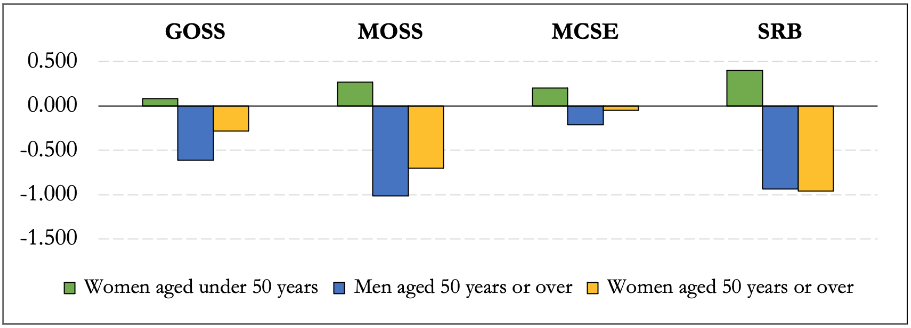

Figure 3: Construct mean scores (reference group = men aged under 50 years)

5 Discussion and Conclusion

In this study, we examined the effects of general online shopping skilfulness, mobile online shopping skilfulness, and multichannel self-efficacy on showrooming behaviour as well as their potential gender and age differences. During this examination, we made three main findings. First, of the examined perceived consumer capabilities, we found mobile online shopping skilfulness to have a strong positive effect on showrooming behaviour, whereas the total effect of general online shopping skilfulness was found to be statistically not significant. In addition, contrary to our hypothesis, we found the effect of multichannel self-efficacy to be negative instead of positive. This negative effect highlights the importance of having general and mobile online shopping skilfulness as controls when examining the effect of multichannel self-efficacy on showrooming behaviour. Without such controls, our findings would have been similar to those by Arora et al. (2017), suggesting only a positive effect (cf. the positive correlation between multichannel self-efficacy and showrooming behaviour in Table 2). In other words, this negative effect reflects other mechanisms through which multichannel self-efficacy affects showrooming behaviour in addition to consumers with higher multichannel self-efficacy also having higher online shopping skilfulness. Two potential examples of such mechanisms are the effects of multichannel self-efficacy on showrooming behaviour via trust and risks. Related to these, Kim and Kim (2005) found online transaction self-efficacy to affect positively the trust toward and negatively the risks of online shopping. Multichannel self-efficacy can be expected to exhibit similar effects because consumers with lower multichannel self-efficacy are likely to be less confident and more uncertain about their use of various offline and online channels. In turn, Daunt and Harris (2017) found lower trust to result in more showrooming behaviour, partly due to the pivotal role of trust in promoting customer loyalty (Harris & Goode, 2004), whereas Arora et al. (2017) have suggested that higher risks result in more showrooming behaviour because consumers typically try to reduce them by spending more time searching for information, which may also involve a visit to a brick-and-mortar store in order to physically examine the products. Thus, both these mechanisms result in a negative effect of multichannel self-efficacy on showrooming behaviour.

Second, although general online shopping skilfulness was found to have no statistically significant total effect on showrooming behaviour, we found it to have a positive effect on multichannel self-efficacy together with mobile online shopping skilfulness. If one assumes a positive association between experience and skilfulness, this finding is largely in line with the prior study by Chiu et al. (2011), who found Internet experience and vicarious experience to positively affect multichannel self-efficacy. Third, in terms of the potential gender and age differences, we found no differences in the effects between the constructs of our research model. However, we found women aged under 50 years to have the highest online shopping skilfulness and multichannel self-efficacy, which also resulted in them practising showrooming most commonly. In addition, we found consumers aged under 50 years to have higher online shopping skilfulness and multichannel self-efficacy in comparison to consumers aged 50 years or over, once again also resulting in them practising showrooming more commonly. These findings conflict with the prior studies by Burns et al. (2019) and Dahana et al. (2018), who found no gender differences in showrooming behaviour. This may be explained by our more detailed examination of also the interactions between gender and age. However, the findings are in line with the prior study by Dahana et al. (2018), who found showrooming behaviour to be more prevalent among younger consumers.

From a theoretical perspective, the aforementioned findings provide valuable new insights into the antecedents of showrooming behaviour and multichannel self-efficacy as well as their potential gender and age differences. From a practical perspective, they also have important implications for the retailers in the novel omnichannel environments, who can utilise them to either promote or reduce showrooming behaviour through manipulating the perceived consumer capabilities, while also simultaneously considering the potential negative side-effects that higher multichannel self-efficacy may have on showrooming behaviour via trust and risks. Moreover, the retailers can also try to steer showrooming behaviour from so-called competitive showrooming to so-called loyal showrooming, in which the final purchase is made from the same retailer whose brick-and-mortar store was visited (Schneider & Zielke, 2020).

6 Limitations and Future Research

We consider this study to have four main limitations. First, the study was conducted by focusing only on Finnish consumers, which may limit the generalisability of its findings. Second, our operationalisation of showrooming behaviour focused only on the use of a smartphone for information search while in-store but not on whether a product that was physically examined offline was actually purchased online, which is something that many may consider a characteristic aspect of showrooming behaviour, although it is not a definitive aspect of showrooming behaviour according to Rapp et al. (2015). Third, our measurement of showrooming behaviour was based on subjective self-reporting instead of objective observations, such as real usage data. Fourth, in our research model, we mainly focused on perceived online consumer capabilities instead of perceived offline consumer capabilities, such as in-store shopping savviness, which was found to have a positive effect on showrooming behaviour in the prior study by Daunt and Harris (2017). Future studies should address these limitations by replicating the study in other countries while revising its research model as well as the operationalisation and measurement of its constructs.

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Appendix A: Item Wordings

Item	Wording
GOSS1	I consider myself knowledgeable about good search techniques for online shopping.
GOSS2	I am extremely skilled at online shopping.
GOSS3	I know how to find what I am looking for when shopping online.
MOSS1	I feel confident using a smartphone to complete an online shopping transaction effortlessly.
MOSS2	I am able to use a smartphone to complete an online shopping transaction in a short time especially if I get some guidance.
MOSS3	I am able to use a smartphone to complete an online shopping transaction in a short time especially if I have used a similar store or system before.
MCSE1	I am confident of my ability to use both online and offline channels while shopping.
MCSE2	I am able to utilise both online and offline channels in the process of purchase.
MCSE3	I believe I am good at evaluating the choices of online and offline channels while shopping.
SRB1	I use mobile devices to find better prices for products online.
SRB2	I often use mobile devices to find more information about products in the store.
SRB3	I use mobile devices to look for information about products while still in the store.