Factors Affecting Adoption of Online Banking: A Meta-Analytic Structural Equation Modeling Study*

Ali Reza Montazemi (montazem@mcmaster.ca)\textsuperscript{a}\textsuperscript{†}, Hamed Qahri-Saremi (hqahr2@uis.edu)\textsuperscript{b}\textsuperscript{1}\textsuperscript{†}

\textsuperscript{a} DeGroote School of Business, McMaster University, 1280 Main Street West, Hamilton, Ontario, Canada L8S 4M4.
\textsuperscript{b} College of Business and Management, University of Illinois at Springfield, One University Plaza, Springfield, Illinois, USA, 62703-5407.

Abstract
Despite the potential benefits that online banking offers consumers, it has low adoption rate. We systematically review online banking adoption literature to propose two research models of factors affecting pre-adoption and post-adoption of the online banking. To test our proposed models, we applied a two-stage random-effects meta-analytic structural equation modeling method to data collected from 25,265 cases from primary empirical studies of online banking adoption. Our findings show that ten factors affect consumers’ adoption of the online banking. Furthermore, we show that the relative importance of these factors differs depending on consumers’ pre-adoption and post-adoption of the online banking.

Keywords: Online Banking, Internet Banking, Mobile Banking, Grounded Theory Literature Review, MASEM, Meta-Analysis, SEM, Continued Use, Adoption, Innovation Diffusion Theory, Intention, Random-effects, Total Effects, Relative Importance.

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\textsuperscript{†} Authors’ contributions to this study are equal and their names are displayed in an alphabetical order.
\textsuperscript{1} Corresponding author at: College of Business and Management, University of Illinois at Springfield, One University Plaza, Springfield, Illinois, USA, 62703-5407.
Phone: +1 (217) 206-8276.
Email address: hqahr2@uis.edu.
1. Introduction

Online banking is expected to appeal to consumers with benefits such as cost savings, greater control over service delivery, reduced wait times, higher perceived levels of customization, and convenient access to services without time or space constraints. This application of information technology appeals to financial institutions because it can standardize service delivery, reduce labor and service costs, expand the options for delivery, and reach consumers who are unreachable through other channels [35]. Notwithstanding its appeal, online banking adoption by consumers is low. According to the research firm comScore [33], 423.5 million people accessed online banking sites globally during April 2012, reaching 28.75% of the Internet users. This consisted of 45% of the Internet users in North America, 37.8% in Europe, 25.1% in Latin America, 22% in Asia Pacific, and 8.8% in Africa. Such a low adoption rate is troublesome for banking institutions [145]. To increase the adoption rate, banks need to better manage factors that affect consumer adoption of the online banking. To that end, scholars have proposed a variety of models to explain the factors affecting consumers’ adoption of the online banking. A recent descriptive literature review shows that the interest in the topic of online banking adoption has grown significantly between 1999 and 2012, and it remains to be a popular research agenda [51]. However, despite more than a decade of research, the extant online banking adoption literature remains somewhat fragmented [36, 51, 135]. Researchers have chosen to study factors of their individual interests and there is no systematic integration among them. Moreover, the growth of the literature increases the likelihood of replicating studies and crosschecking the effects of factors across studies. At the same time, we begin to observe relationships that are inconsistent or even contradict one another across studies. For example, Gu et al. [50] identify trust in the physical bank as a key antecedent of consumer’s intention to use the online banking. In contrast, Luo et al. [94] show that trust in the physical bank has no significant effects on consumer’s intention to use the online banking. Systematic meta-analysis is likely to help us ameliorate these problems.

Meta-analysis is a method for reviewing a domain of scientific literature and quantitatively determining the degree to which a particular finding has been successfully replicated [39]. Meta-analysis extends knowledge by clarifying and quantitatively synthesizing existing research findings [39]. It has gained a widespread recognition as an indispensable tool for quantitatively integrating knowledge garnered in different empirical studies on a topic [39, 53]. The widespread use of meta-analysis in the technology adoption literature (see Appendix A, Table A1) attests to its growing stature in this field as a tool for synthesizing the accumulated knowledge, explaining the inconsistent findings, and identifying gaps in the literature for future research. Moreover, structural research models can be tested using structural equation modeling (SEM) after meta-analysis has summarized the relationships of interest [28, 39, 120]. SEM can illuminate or eliminate certain theoretical explanations, which advance researchers’ knowledge and understanding of the literature. In this paper, we address two research questions: (1) What factors affect the consumers’ pre- and post-adoption of the online banking? (2) What is the relative importance of each factor on the consumers’ pre- and post-adoption of the online banking? To answer these research questions, we use innovation diffusion theory [2, 113] as our theoretical foundation, and “Grounded Theory Literature Review” [100, 142] and meta-analytic structural equation modeling (MASEM) [27, 28] as our methods to systemically and quantitatively synthesize the primary empirical studies pertinent to the online banking adoption.
Diffusion of an innovation involves a process that occurs over time and consists of two stages – pre- and post-adoption [64, 113], with actions and decisions occurring at each stage. The pre-adoption stage begins with consumers’ awareness that leads to mental evaluation, which in turn may lead to the adoption of the innovation [89]. The post-adoption of the innovation consists of trial that may lead to the continued use of the innovation [89]. Guided by the innovation diffusion theory as the theoretical foundation, this paper systematically reviews the extant online banking adoption literature using Grounded Theory Literature Review method and proposes two research models. The first research model pertains to the factors affecting the pre-adoption and the second research model deals with the factors affecting the post-adoption of the online banking. To that end, we identified 29 empirical studies examining 7,151 cases of the pre-adoption intention to use and 52 empirical studies examining 18,114 cases of the post-adoption intention to continue use of the online banking. These studies have proposed a variety of different models to explain the factors affecting the adoption of the online banking. To quantitatively synthesize the literature, we subject our two proposed research models to two-stage random-effects MASEM analyses. MASEM refers to the meta-analytic methods that use SEM for quantitatively contrasting and combining results from different studies to identify patterns among study results, sources of disagreement among those results, and other interesting relationships that may come to light in the context of multiple studies [28].

The remainder of this paper proceeds as follows. Section 2 explains our theoretical foundation for this study and proposes two research models to investigate the factors affecting the pre- and post-adoption of the online banking. In section 3, we explain the Grounded Theory Literature Review method adapted for our theory-driven review of online banking adoption literature towards identifying and synthesizing the factors affecting the pre- and post-adoption of the online banking. Furthermore, we explain and apply the two-stage random-effects MASEM method to test our two proposed research models with data collected from 29 independent empirical studies of pre-adoption and 52 independent empirical studies of the post-adoption of the online banking. Findings from our two-stage random-effects MASEM analyses are presented in section 4. Section 5 provides a discussion of our findings and their implications for theory and practice. Section 6 explains the study limitations with the recommendations for future research, followed by section 7, which concludes the paper.

2. Theoretical Foundation

Innovation diffusion theory posits that the pre-adoption stage of the innovation adoption process entails the consumer’s decision whether to accept or reject to adopt the innovation, and post-adoption stage of the innovation adoption process entails consumer’s decision whether to continue or discontinue using the innovation. Three innovation characteristics – relative advantage, complexity, and compatibility – have been related consistently to the both stages of the innovation adoption process [2, 134]. Relative advantage captures the extent to which a consumer views the innovation as offering an advantage over previous ways of performing the same task [2]. Relative advantage is similar to the notion of usefulness in the technology acceptance model (TAM) [29]. Rogers’ [113] notion of complexity, the second innovation characteristic, is similar to the ease of use factor in TAM that pertains to the degree to which a consumer views usage of the target technology to be relatively free of effort [37]. Innovations that are perceived to be more useful and easier to use have a higher likelihood of being accepted and used by consumers, at the both stages of the innovation adoption process [2]. The third
innovation characteristic that affects consumer’s adoption decision is compatibility [113, 134]. Compatibility is a multidimensional construct defined as the degree to which using an innovation is consistent with the existing sociocultural values and beliefs, past and present experiences, and needs of consumers [113]. Innovations are inherently uncertain and risky and there is no guarantee that their adoption will in fact produce the anticipated benefits [2]. Compatibility captures the degree of disruption and the magnitude of change the individual is likely to experience when using a new technology [63]. An innovation that is less compatible is more uncertain to the consumers [113]. Uncertainty makes consumers reluctant to engage in online exchange relationships with service providers, especially for high-involvement technologies such as the online banking [109]. To that end, Rogers described the innovation diffusion process as “an uncertainty reduction process” [113] (p. 232). In this study, we draw on the three aforementioned dimensions of innovation diffusion theory, namely relative advantage, complexity, and compatibility, as our theoretical foundation to identify and synthesize the factors that affect consumers’ pre- and post-adoption of the online banking.

To that end, we used Grounded Theory Literature Review method [100, 142] to perform a thorough and theoretically relevant analysis of the extant online banking adoption literature to identify and synthesize the factors that affect consumers’ pre- and post-adopter of the online banking. As a result, we have identified perceived usefulness factor in the extant online banking adoption literature that represents the relative advantage dimension of innovation diffusion theory; perceived ease of use factor that represents the complexity dimension of innovation diffusion theory; and trust, personal innovativeness, and social influence factors that mitigate uncertainty in the adoption of the online banking, thus represent the compatibility dimension of innovation diffusion theory, towards pre- and post-adoption of the online banking. Additionally, we have identified systems quality, information quality, and service quality as factors that mitigate uncertainty in the continued use of the online banking, thereby represent the compatibility dimension of innovation diffusion theory towards post-adoption of the online banking. Next, we elaborate on these factors to postulate 34 hypotheses to illuminate their effects on consumers’ pre- and post-adoption of the online banking. The details of the procedures based on Grounded Theory Literature Review method for identifying the aforementioned factors that represent the three dimensions of innovation diffusion theory in the extant online banking adoption literature is detailed in the methodology section (i.e., section 3.1 of this paper).

2.1. Pre-Adoption Stage of the Online Banking: Hypotheses and Research Model 1

Drawing on TAM [37], perceived usefulness and perceived ease of use affect consumers’ intention to adopt a technology. Furthermore, the less effort that consumers expect to invest in using the technology, the more useful they perceive it to be [37]. Thus, we can postulate the following three hypotheses, as depicted in Fig. 1:

Hypothesis 1. Consumers’ perceived usefulness of the online banking positively affects their intention to use the online banking at the pre-adoption stage.

Hypothesis 2. Consumers’ perceived ease of use of the online banking positively affects their intention to use the online banking at the pre-adoption stage.

Hypothesis 3. Consumers’ perceived ease of use of the online banking positively affects their perceived usefulness of the online banking at the pre-adoption stage.
Fig. 1. Our proposed research model 1

Trust is crucial in many of the economic activities that involve uncertainty in regard to their outcomes [48]. This is even more the case with the online banking – a sector that consumers can perceive as being high risk [96], because the temporal and the spatial separation between the consumers and the physical bank does not allow consumers to evaluate the transactional situation as in a face-to-face interaction with the physical bank personnel. Based on the systematic review of the online banking adoption literature (see section 3.1 in methodology for details), we have identified four dimensions of trust pertinent to the online banking adoption: (i) trust in the online banking, (ii) trust in the physical bank, (iii) structural assurances, and (iv) consumers' propensity to trust.

(i) Trust in the online banking – The prominence of trust in the online banking can be explained through the lens of social exchange theory [40, 45]. Social exchange theory views interactions in a similar manner to economic exchanges: being composed of costs paid and rewards received. As in an economic exchange, people take part in an interaction only if their outcome from it is satisfactory – i.e., if their perceived rewards exceed their perceived costs [45, 56]. Unlike an economic exchange, however, a social exchange deals with situations where there is no explicit or detailed legal contract binding the parties or when the contract is insufficient to provide a
complete legal protection to all of the parties involved. Since rewards cannot be guaranteed in a social exchange, trust is essential and determines individuals’ expectations from the relationship [13, 45]. Trust increases the perceived certainty concerning other party’s expected behavior and reduces the fear of being exploited, especially when the social exchange involves current costs (e.g., risks) invested in exchange for expected future unguaranteed rewards [45, 69]. In the online environment, consumers and online retailers often face spatial and temporal separation; consequently, transactions carried out online often do not involve a simultaneous transaction of goods (or services) and money [147]. Fears of hackers and privacy invasion compound the uncertainty surrounding online services [55, 147]. Thus, trust in the online banking is essential to mitigate the uncertainty of financial transactions to entice the consumer to use it [71]. To this end, we postulate the following hypothesis, as depicted in Fig. 1:

**Hypothesis 4.** Consumers’ trust in the online banking positively affects their intention to use the online banking at the pre-adoption stage.

**(ii) Trust in the physical bank** – Prior to adopting the online banking, consumers typically have a history of experience with the traditional brick & mortar bank (i.e., physical bank). To mitigate the uncertainty in regard to the online banking, consumers are likely to draw upon their trust in the physical bank to infer about the operations of the online banking [29]. Having high trust in the physical bank could lead the consumers to have both a high trust in the online banking and a high intention to adopt the online banking [71]. Based on this justification, we postulate the following two hypotheses, as depicted in Fig. 1:

**Hypothesis 5.** Consumers’ trust in the physical bank positively affects their intention to use the online banking at the pre-adoption stage.

**Hypothesis 6.** Consumers’ trust in the physical bank positively affects their trust in the online banking at the pre-adoption stage.

**(iii) Structural Assurances** – The smooth and secure processing of online transactions depends on the functioning of the hardware and software as well as on the security of the data exchange services including the cryptographic protocols that are used [99]. Online banks can mitigate consumers’ uncertainty about the security and privacy of their technological infrastructure and services by providing structural assurances [99]. This includes safety nets, guarantees, regulations, and security resources in place to promote a sense of security and privacy about the pertinent technological infrastructure used. Thus, lack of structural assurances increases the uncertainty about the security and privacy of the online interactions and transactions with the online banking that hinders consumers’ trust in the online banking [71]. To this end, we postulate the following hypothesis, as depicted in Fig. 1:

**Hypothesis 7.** Structural assurances built into the online banking system positively affect consumers’ trust in the online banking at the pre-adoption stage.

**(iv) Consumers’ propensity to trust** – This dimension of trust represents a consumer's general tendency to trust others, which is a personal trait [94, 96]. Consumers with higher tendency to trust others are expected to develop higher trust in the online banking [94], as well as the physical bank. Thus, we postulate the following hypotheses, as depicted in Fig. 1:

**Hypothesis 8.** Consumers' propensity to trust positively affects their trust in the online banking at the pre-adoption stage.
Hypothesis 9. Consumers’ propensity to trust positively affects their trust in the physical bank at the pre-adoption stage.

Personal innovativeness represents the degree to which an individual is willing to try out a new innovation [2]. Agarwal and Prasad [2] contend that personal innovativeness influence the individual’s perceptions about a new information technology. They identify personal innovativeness as symbolizing the risk-taking propensity that exists in certain individuals and not in others. Furthermore, innovation diffusion theory [113] explains that more innovative individuals are more active information seekers of the new ideas and that they adopt the innovations earlier than others – they are early adopters [113]. Innovation diffusion theory also explains that early adopters are more technically competent than others [148]. Thus, given their technical competencies, early adopters would consider the complexity of the information technology innovations less troublesome than others, suggesting a direct influence on the perceived ease of use of the information technology innovations [148]. To this end, Lu et al. [92] and Lewis et al. [83] found that personal innovativeness is a significant determinant of perceived ease of use of information technology. Furthermore, innovative individuals typically have the ability to envision the potential benefits and advantages associated with an innovation in its early stage of diffusion [148]. Empirical findings show a significant positive relationship between consumers’ personal innovativeness and their perceived usefulness of a new information technology [92]. Thus, we postulate the following hypotheses, depicted in Fig. 1:

Hypothesis 10. Consumers’ innovativeness positively affects their perceived ease of use of the online banking at the pre-adoption stage.

Hypothesis 11. Consumers’ innovativeness positively affects their perceived usefulness of the online banking at the pre-adoption stage.

Social influence mitigates consumers’ uncertainty in innovation adoption [92]. Social influence refers to the perceived influence from social networks and important others for/against a certain behavior [92]. The justification is that an innovation, such as the online banking, creates uncertainty about the expected outcomes for consumers. Because consumers are generally uncomfortable with the uncertainty, they tend to interact with their social network to consult on their adoption decisions [92]. The significance of social influence on consumers’ adoption decisions can be further explained from the lens of social information processing theory. Social information processing theory [117] posits that individuals adapt their attitudes, behavior, and beliefs to their social context. Drawing on this theory, Fulk and his colleagues [44] suggest that “information passed through individual’s social networks influences their perceptions of a target technology” [92] (p. 250). Furthermore, there are empirical evidences that social influence positively influences perceived usefulness [90, 138], perceived ease of use [90, 92], and the trusting beliefs towards a new information technology [84]. Based on the above justifications, we postulate the following hypotheses in the context of the online banking, as depicted in Fig. 1:

Hypothesis 12. Social influence positively affects consumers’ perceived usefulness of the online banking at the pre-adoption stage.

Hypothesis 13. Social influence positively affects consumers’ trust in the online banking at the pre-adoption stage.

Hypothesis 14. Social influence positively affects consumers’ perceived ease of use of the online banking at the pre-adoption stage.
The foregoing hypotheses, depicted in Fig. 1, are concerned with the pre-adoption stage of the online banking. Next, we present the pertinent hypotheses to the post-adoption stage of the online banking, depicted in Fig 2.

2.2. Post-Adoption Stage of the Online Banking: Hypotheses and Research Model 2

As can be noted from Fig. 2, our second proposed research model includes the same factors and hypotheses that we elaborated for the first proposed research model in the section 2.1. Therefore, for parsimony, these hypotheses are stated in Table 1 along with their supporting literature. This allows us to focus on the justification of the factors and the hypotheses that are unique to our proposed research model 2, as follows.

Fig. 2. Our proposed research model 2
Table 1
Hypotheses for our proposed research model 2

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Supporting Literature</th>
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<tr>
<td><strong>Hypothesis 15.</strong> Consumers’ perceived usefulness of online banking</td>
<td>[12, 21, 34, 50, 77, 88, 111]</td>
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<td>positively affects their continued use intention of the online banking at</td>
<td></td>
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<tr>
<td>the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 16.</strong> Consumers’ perceived ease of use of online banking</td>
<td>[50, 77, 88, 111]</td>
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<tr>
<td>positively affects their continued use intention of the online banking at</td>
<td></td>
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<tr>
<td>the post-adoption stage.</td>
<td></td>
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<tr>
<td><strong>Hypothesis 17.</strong> Consumers’ perceived ease of use of online banking</td>
<td>[21, 34, 50, 77, 88, 111]</td>
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<tr>
<td>positively affects their perceived usefulness of the online banking at the</td>
<td></td>
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<tr>
<td>post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 18.</strong> Consumers’ trust in the online banking positively</td>
<td>[50, 88, 132, 136]</td>
</tr>
<tr>
<td>affects their continued use intention of the online banking at the post-</td>
<td></td>
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<td>adoption stage.</td>
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<td><strong>Hypothesis 19.</strong> Consumers’ trust in the physical bank positively</td>
<td>[29, 71, 80]</td>
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<td>affects their continued use intention of the online banking at the post-</td>
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<td>adoption stage.</td>
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<td><strong>Hypothesis 20.</strong> Consumers’ trust in the physical bank positively</td>
<td>[29, 50, 88]</td>
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<td>affects their trust in the online banking at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 21.</strong> Structural assurances built into the online banking</td>
<td>[19, 50, 60, 65, 88, 136, 151]</td>
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<td>system positively affect consumers’ trust in the online banking at the</td>
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<td>post-adoption stage.</td>
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<td><strong>Hypothesis 22.</strong> Consumers’ propensity to trust positively affects their</td>
<td>[88, 119]</td>
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<td>trust in the online banking at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 23.</strong> Consumers’ propensity to trust positively affects their</td>
<td>[88]</td>
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<td>trust in the physical bank at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 24.</strong> Social influence positively affects consumers’</td>
<td>[4, 5, 24, 50, 92]</td>
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<tr>
<td>perceived usefulness of the online banking at the post-adoption stage.</td>
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<td><strong>Hypothesis 25.</strong> Social influence positively affects consumers’ trust</td>
<td>[60]</td>
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<td>in the online banking at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 26.</strong> Social influence positively affects consumers’</td>
<td>[4, 5, 92]</td>
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<td>perceived ease of use of the online banking at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 27.</strong> Consumers’ innovativeness positively effects their</td>
<td>[6, 92]</td>
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<td>perceived ease of use of the online banking at the post-adoption stage.</td>
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<tr>
<td><strong>Hypothesis 28.</strong> Consumers’ innovativeness positively affects their</td>
<td>[6, 92]</td>
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<td>perceived usefulness of the online banking at the post-adoption stage.</td>
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The difference between our two research models is addition of system quality, information quality, and service quality for the post-adoption of the online banking. These factors are predicated on consumers’ direct experience and interaction with the online system [14]. Schema theory [115] enables us to explain the significance of these factors towards post-adoption of the online banking. A schema is a framework of organized concepts that are individuals’ representation of their experience [144]. Louis and Sutton [91] expand on this definition, positing that a schema is “a cognitive structure that provides situational forecasts on which individuals rely” (p. 61). Research has shown that schemata are effective tools for interpreting the world and play an important role in value judgments across multiple fields [144]. Xu et al. [144] suggest that three dimensions of information systems quality (i.e., system quality, information quality, and service quality) determine the schemata that consumers are likely to rely on towards adopting an online system. Extant research findings also demonstrate the importance
of the role played by the three dimensions of information systems quality in mitigating consumers’ uncertainty towards the post-adoption use of the online systems [14, 68, 92, 133]. Extrapolating this argument for online banking context, we contend that consumers' perceptions of system quality, information quality, and service quality of the online banking influence their post-adoption of the online banking, as follows.

(i) **System Quality** focuses on the technical aspect of the provider’s online system and is defined as the extent to which the online system possesses the attributes of reliability [50], accessibility [14, 38, 73], speed [14, 49, 149, 156], flexibility [73], aesthetics [47, 156], and navigation [38, 47, 131, 133, 156]. A well-constructed online system provides consumers with more convenience, reliability, and faster responses, which makes interaction with the online system easier for the consumers [52]. Based on the above justification, we propose the following hypothesis in the context of the online banking, as depicted in Fig. 2:

**Hypothesis 29.** System quality positively affects consumers’ perceived ease of use of the online banking at the post-adoption stage.

(ii) **Information Quality** focuses on the content of the provider’s online system and represents the extent to which the online content possesses the attributes of accuracy, timeliness, completeness, relevance, and consistency [14, 38, 133]. During the direct interaction with the online system, consumers process its content – information – to make decisions [123]. Higher quality of information would make the online system more useful for decision-making [3]. Furthermore, high quality of the online system information (e.g., accuracy of transaction records) would create an impression of competency and integrity of the online provider, which would result in consumers' trust in the online provider [14]. To that end, we postulate the following two hypotheses in the context of the online banking, as depicted in Fig. 2:

**Hypothesis 30.** Information quality positively affects consumers’ perceived usefulness of the online banking at the post-adoption stage.

**Hypothesis 31.** Information quality positively affects consumers’ trust in the online banking at the post-adoption stage.

(iii) **Service Quality** indicates the quality of overall support and services delivered by the online service provider [38, 133]. In particular, service quality represents the provision of mechanisms for receiving consumers' requests/complaints and their timely resolution. It also involves assisting consumers in the effective use of the online system, suggesting complementary services, and jointly solving consumers' problems [3]. The proposed metrics for service quality are responsiveness (i.e., providing prompt response to consumers' requests), assurance (i.e., having the required knowledge for responding to consumers' requests), and empathy (i.e., having consumers' best interests at heart) [38]. If consumers feel an online service provider is responsive to their particular requests, reassuring, and emphatic in caring for them as individuals, then the risk of patronizing that online service would be reduced [32]. Higher levels of service quality assist the consumers to resolve their problems more promptly, which makes the online banking easier to use [3]. It also helps the consumers to use the online banking more effectively [3], which makes the online banking more useful for the consumers. Moreover, higher level of service quality is expected to generate an impression of competency and benevolence of the online service provider, which would improve consumers' trust in the online service provider [70]. Based on the above justifications, we postulate the following hypotheses in the context of the online banking, as depicted in Fig. 2:
**Hypothesis 32.** Service quality positively affects consumers’ perceived ease of use of the online banking at the post-adoption stage.

**Hypothesis 33.** Service quality positively affects consumers’ perceived usefulness of the online banking at the post-adoption stage.

**Hypothesis 34.** Service quality positively affects consumers’ trust in the online banking at the post-adoption stage.

### 3. Methodology

We drew on Grounded Theory Literature Review method [100, 142] to identify and synthesize the factors affecting consumers’ pre- and post-adoption of the online banking, as presented in our two proposed research models depicted in Fig. 1 and Fig. 2. Next, we used two-stage random-effects MASEM method [27, 28, 98, 99] that combines random-effects meta-analytic techniques with structural equation modeling (SEM) to meta-analytically test our two proposed research models.

#### 3.1. Grounded Theory Literature Review Method

We used Grounded Theory Literature Review method [100, 142] to perform a thorough and theoretically relevant analysis of the extant online banking adoption literature in order to identify and synthesize the factors that affect consumers’ pre- and post-adoption of the online banking. Grounded Theory Literature Review method was implemented in five steps, depicted in Fig. 3. Step 1 (“Define”) consisted of defining the criteria for inclusion, determining the pertinent databases of the online banking studies for search, and determining the appropriate search terms. In step 2 (“Search”), the actual search for the pertinent primary studies was performed using the keywords and the pertinent databases determined in the step 1. In step 3 (“Select”), the retrieved studies from step 2 were refined using the inclusion criteria that were determined in step 1. Next, in step 4 (“Analyze”), the refined sample of the pertinent studies was synthesized using Grounded Theory techniques in order to identify and synthesize the factors that affect consumers’ pre- and post-adoption of the online banking. Finally, in step 5 (“Present”), the factors identified from the synthesis of the pertinent online banking studies in step 4 were used to propose two research models for this study, as depicted in Fig. 1 and Fig. 2 and explained in the “Theoretical Foundation” section of this paper (see section 2 for details). Details of the five aforementioned steps, depicted in Fig. 3, in support of the procedures for the synthesis of the extant online banking adoption literature are presented next.
3.1.1. Steps 1 – 3: Define, Search, and Select

To identify studies that investigated the online banking adoption, we searched online databases (e.g., EBSCOhost, JSTOR, Scholar’s Portal, Google Scholar, AIS, ACM, ScienceDirect, Palgrave Macmillan, Extenza, Metapress, Highwire Press, Sage, Emerald, IEEE, INFORMS, InterScience, Factiva, Gale Cengage) and digital theses libraries (e.g., ProQuest, WorldCat). To that end, we used as search terms several variations of “online banking” (i.e., “electronic banking”, “online banking”, “self-served banking”, “retail banking”, “Internet banking”, “mobile banking”), “adoption”, “pre-adoption”, “post-adoption”, “acceptance”, “initial use”, and “continued use”. Bibliographies of identified studies were also scanned to locate additional studies. Because it is widely accepted that journals are more likely to publish studies with significant effect sizes, we considered conference proceedings, working papers, and dissertations in order to minimize the potential of biasing our data [98, 99]. We also posted requests to various listservs (e.g., AOM’s OCIS and IDT, AIS ISWorld). The search initially yielded 332 primary studies broadly discussing the Internet and mobile banking. The studies were then examined for inclusion in our study, using the inclusion criteria.

Not all the studies retrieved were appropriate for inclusion in our analysis. Recognizing this, Rosenthal [114] and Wolfswinkel et al. [142] recommended that researchers assess quality of the primary studies by (i) establishing criteria for inclusion, (ii) using a multiple-rater technique to evaluate data from primary studies, and (iii) assessing inter-rater reliability. To that end, we
established four criteria for inclusion of studies in each of the two stages of the online banking adoption (i.e., pre-adoption of the online banking and post-adoption of the online banking). Specifically for the pre-adoption of the online banking, we included only studies in which (1) the context was pre-adoption of the Internet banking and/or mobile banking in the business to customer (B2C) sector, (2) the respondents had unrestrained access to the Internet and/or mobile banking, but had not used it, (3) the analysis was quantitative and provided correlations, sample sizes, and reliabilities, or sufficient data to compute these effect sizes (see Appendix B for details), and (4) measurements exhibited average reliability (Cronbach’s alpha) of at least 0.70 [98, 102]. Similarly, for the post-adoption of the online banking, we included only studies in which (1) the context was post-adoption of the Internet banking and/or mobile banking in the business to customer (B2C) sector, (2) the respondents had prior experience with using the Internet and/or mobile banking, (3) the analysis was quantitative and provided correlations, sample sizes, and reliabilities, or sufficient data to compute these effect sizes (see Appendix B for details), and (4) measurements exhibited average reliability (Cronbach’s alpha) of at least 0.70. Applying the foregoing criteria to the 332 primary studies resulted in 29 pre-adoption and 52 post-adoption primary online banking studies.

3.1.2. Step 4: Analyze

The constructs used in the 29 pre-adoption and 52 post-adoption primary studies were initially identified and coded. Next, we synthesized the identified constructs into factors based on their conceptual similarities and selected the relevant factors to the innovation diffusion theory, as our theoretical foundation, to be included in our two research models, using three Grounded Theory techniques: (1) open coding, (2) axial coding, and (3) selective coding, as explained next.

We used open coding technique, through which constructs and their measurement instruments were coded in each of the 29 pre-adoption and 52 post-adoption primary studies. As a result, we coded 188 constructs in the pre-adoption studies and 277 constructs in the post-adoption studies. Next, we applied axial coding technique to synthesize the identified constructs based on their conceptual similarities. To that end, we drew on the constructs’ measurement instruments used in the primary studies, rather than on merely the authors’ labels assigned to their constructs, for two reasons. Firstly, constructs with different labels in the online banking literature could measure similar concepts, thus can be synthesized under one factor, while constructs with similar labels could measure different concepts, thus should be synthesized under different factors [98, 100, 154]. Secondly, similar to other meta-analytic studies (e.g., [105]), combining multiple conceptually similar constructs of the same factor enabled us to achieve higher content validity for the factors in our study [105]. The content validity of each of the factors in our study are higher than other primary online banking studies because we captured not just one specific attribute of a factor, but a comprehensive set of conceptually similar attributes that were used in the online banking literature for operationalizing that factor. For example, system quality for the online banking has been measured in the extant literature by using constructs such as: reliability [50], accessibility [73], speed [49, 149, 156], flexibility [73], aesthetics [47, 156], and navigation [47, 131, 156]. We synthesize all these constructs in our study to represent system quality factor. As a result, content validity pertinent to the data representing system quality factor in our analyses is higher than each individual study from which the data were collected. To that end, we read through the constructs’ measurement instruments in each of the 29 pre-adoption and 52 post-adoption primary studies and assessed their conceptual similarities and differences, which resulted in identifying 22 and 25
conceptually distinct factors for pre-adoption and post-adoption of the online banking, respectively. Finally, selective coding technique was used to map the identified factors on the three dimensions of the innovation diffusion theory as our theoretical foundation, namely relative advantage that captures the extent to which a consumer views the innovation as offering an advantage over previous ways of performing the same task [2], complexity that captures the extent to which a consumer views the innovation as easy to use [2], and compatibility that captures the extent of uncertainty faced by the consumers in the pre- and post-adoption of an innovation [63, 113]. To that end, we selected the pre- and post-adoption factors that conceptually mapped to any of the three dimensions of the innovation diffusion theory to be included in our two research models for pre- and post-adoption of the online banking.

3.1.3. Step 5: Present

As a result of the four aforementioned steps, we hypothesized intention to use the online banking, perceived usefulness of the online banking, perceived ease of use of the online banking, trust in the online banking, trust in the physical bank, structural assurances, consumers’ propensity to trust, consumers’ innovativeness, and social influence as the factors affecting pre-adoption of the online banking in our research model 1, depicted in Fig. 1 (see Table C1 in Appendix C for the reference operationalizations of the selected factors in our research model 1). Similarly, we hypothesized continued use intention of the online banking, perceived usefulness of the online banking, perceived ease of use of the online banking, trust in the online banking, trust in the physical bank, structural assurances, consumers’ propensity to trust, consumers’ innovativeness, social influence, system quality, information quality, and service quality as the factors affecting post-adoption of the online banking in our research model 2, depicted in Fig. 2 (see Table C1 in Appendix C for the reference operationalizations of the selected factors in our research model 2). The justifications for the hypotheses in our both research models are discussed in the “Theoretical Foundation” section.

3.2. Two-Stage Random-Effects MASEM Method

After identifying the pertinent factors affecting the pre- and post-adoption of the online banking and theoretically hypothesizing their relationships in our two proposed research models, depicted in Fig. 1 and Fig. 2, we adopted two-stage random-effects MASEM method to meta-analytically test our two research models, using a two-stage process [27, 28, 98, 99]. Two-stage random-effects MASEM technique refers to the method focused on synthesizing matrices of effect sizes from multiple primary studies and use it to assess a set of hypotheses in a theoretical structural model [27]. Prior research shows that meta-analysis is an effective instrument for statistically testing a new theory [62, 98]. Furthermore, application of two-stage random-effects MASEM to assess our hypotheses has several advantages over conducting a primary study (see Appendix D for details):

1) Accumulation of multiple samples through two-stage random-effects MASEM increases the sample size and bolsters a model test’s statistical power relative to that of single-sample studies [98, 99]. Two-stage random-effects MASEM can therefore detect valid effects that studies with modest sample sizes fail to detect [98, 99]. By cumulating studies before model estimation, taking into account uneven sample sizes, our meta-analysis can generate more robust model estimates

2) Meta-analytical corrections for the artifacts, such as sampling errors, improve the accuracy of parameter estimates [98, 99].

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3) A joint SEM and meta-analytic approach in the two-stage random-effects MASEM embodies a more complete picture and precise test of the entire structural model than either technique might achieve alone. Neglecting interdependency among measured effects, bivariate meta-analytic estimates of individual relationships between variables imprecisely capture the unique effect size of the relationship, whereas sampling error may influence SEM estimates derived from a single sample [98, 99]. Together, meta-analytic artifact corrections yield more credible empirical data for SEM analysis, which more accurately assesses structural parameters (given a correctly specified model) [98, 99].

We assess the 34 stated hypotheses (depicted in our two research models in Fig. 1 and Fig. 2) using the two-stage random-effects MASEM technique [27, 99] as per following steps (see Appendix D for details):

1) Coding the effect sizes from the pertinent primary studies in the separate datasets for testing each of our two research models (depicted in Fig. 1 and Fig. 2).
2) Evaluation of measurement invariability for each of the factors in our research models (stage 1 of our two-stage random-effects MASEM analysis).
3) Evaluation of our both research models, using SEM (stage 2 of our two-stage random-effects MASEM analysis).

3.2.1. Coding of data from pertinent primary studies for MASEM analysis

We coded the data and ran the two-stage random-effects MASEM analysis separately and independently for each of our two research models, depicted in Fig 1 and Fig. 2. To facilitate the two-stage random-effects MASEM analysis, we followed the data-coding procedure specified by Cheung [26]. Accordingly, for our research model 1, we coded a 8×8 matrix of bivariate correlations (among the eight dimensions in the research model 1) for each study based on the bivariate correlations supplied by each study. There were insufficient data to include “consumers’ innovativeness” in the pooled correlation matrix for our research model 1, depicted in Fig. 1. Therefore, this factor and its related hypotheses (H10 and H11) were dropped from further analysis. "NA" was coded for any missing pairings in the respective study so that the missing values would not affect pooled correlations [26, 98]. Sample sizes and measurement reliabilities were also coded for each study.

Similarly, for our research model 2, we coded a 10×10 matrix of bivariate correlations (among the ten dimensions in our research model 2) for each study based on the bivariate correlations supplied by each study. There were insufficient data to include “consumers’ innovativeness” and “consumers’ propensity to trust” in the pooled correlation matrix for our research model 2, depicted in Fig. 2. Therefore, these factors and their related hypotheses (H22, H23, H27, and H28) were dropped from further analysis. "NA" was coded for any missing pairings in the respective study [26, 98]. Sample sizes and measurement reliabilities were also coded for each study. Next, we followed the two-stage process for the random-effects MASEM: in stage one we evaluated the measurement invariability for our research models and in stage two we tested the structural models using SEM, as follows.

3.2.2. Evaluation of measurement invariability for the factors in our research models (stage one analysis)

Notwithstanding the advantages of using a meta-analytic technique for testing a new theory (as previously discussed), the potential exists that the pooling of data from multiple primary studies could introduce artifacts into SEM parameter estimates. Drawing on Hunter and Schmidt
prior studies have identified six artifacts that potentially affect meta-analytic tests of a new theory: (1) non-independence of data sets, (2) coding errors, (3) multicollinearity, (4) missing studies, (5) type II error, and (6) heterogeneity of effect-sizes across primary studies included in the MASEM. As elaborated next, we took rigorous precautions to address each of the foregoing six artifacts in order to be confident that the final parameter estimates are the results of the relationships hypothesized in our theoretical models rather than undesired artifacts.

3.2.2.1. Ensuring independence of data sets – Non-independence of data sets would violate an important assumption in meta-analytic analyses [143]. Therefore, we applied the following criteria to ensure the independence of the data sets from the primary studies included in our two-stage random-effects MASEM. We included only one data set if two or more primary studies used the same sample [143]. Conversely, for primary studies that presented two separate samples for two different contexts (e.g., Susanto et al. [131]), we retained two separate data sets. Similarly, when a study presented one set of correlations for the pre-adoption and another separate set of correlations for the post-adoption of the online banking, the two data sets were retained separately in our MASEM analyses for the corresponding research models. This approach is considered appropriate and does not violate the independence assumption [58, 98]. As a result of applying the preceding criteria, our sample for the research model 1 depicted in Fig. 1 contained 29 data sets (k) comprised of 7,151 cases (N) and our sample for the research model 2 depicted in Fig. 2 contained 52 data sets (k) comprised of 18,114 cases (N) for random-effects MASEM. An asterisk (*) in the reference section marks each study contributing data for our two-stage random-effects MASEM analysis.

3.2.2.2. Coding Process – As recommended by [78], each of the two authors independently assessed (i) the selection and independence of the primary studies, (ii) the conceptual consistency of factor operationalizations (i.e., constructs) in each primary study to the operationalizations of the factors in this study, and (iii) the coding of effect sizes from the primary studies for MASEM analysis. For example, each rater independently mapped the factors operationalizations from the primary studies to the operationalizations of our factors and coded correlations, reliabilities and sample sizes from each primary study. Disagreements were resolved by adopting a consensus approach. Resolving discrepancies in this way is considered a “superior way to correct coding mistakes” ([78], p. 1521). As per Hunter and Schmidt [58], we also assessed the coded data for outliers that could indicate inconsistent operationalizations (i.e., measurement artifacts). We further reviewed the operationalizations of outliers and retained only operationalizations that both authors unanimously accepted as consistent with our reference operationalizations (see Table C1 in Appendix C).

3.2.2.3. Assessing Multicollinearity – We reviewed our pooled correlation matrices for each of our two proposed research models for multicollinearity. The purpose of checking for multicollinearity was to make sure that the factors in each of our two proposed research models are distinct. Based on the extant literature, we know that the factors in our two proposed research models are well-established distinct factors. Nonetheless, we tested for the multicollinearity by checking the pooled correlation coefficients and also by calculating variance inflation factor (VIF) [97]. All factor pairs in our both pooled correlation matrices exhibited $r<0.68$ and $VIF<1.87$ [97]. Hence, we were satisfied that the data did not violate the SEM assumption of independence of factors (i.e., absence of multicollinearity) (See Appendix C for details).

3.2.2.4. Assessing potential missing-studies artifacts – In a meta-analysis, the potential exists for a “file drawer problem” (i.e., missing-studies artifact), in which studies that find non-significant effects for our hypothesized relationships are not identified [98]. As elaborated in
Appendix C, we ensured that this issue does not affect our results by using the formula presented by Hunter and Schmidt [58] (formula 13.2b on p. 501) to calculate the “fail-safe” K values for each of our hypothesized relationships based on their available effect sizes (i.e., correlation coefficients collected from the primary studies). The Fail-safe K value estimates the number of missing studies with null findings that could possibly render a relationship non-significant [58, 104]. The high fail-safe Ks for our hypothesized relationships (reported in Tables C2a and C2b in Appendix C) provide confidence in the robustness of our results with respect to the possible missing studies.

3.2.2.5. Assessing Type II error – An important component of the statistical test is the notion of statistical power, defined as the probability that the results of a statistical test will not lead to acceptance of the null hypothesis when it is in fact false (i.e., Type II error) [98]. To assess the risk of Type II error, we calculated the statistical power of pooled correlations for each of our hypotheses based on respective pooled sample sizes [98]. The results of our power analyses (reported in Tables C2a and C2b in Appendix C) exceeded 0.80 – a widely accepted threshold for the required level of statistical power [11]. Therefore, we are confident that our MASEM analyses for both of our research models have sufficient power to reject rather than accept null hypotheses that are truly false [98].

3.2.2.6. Addressing the heterogeneity of effect sizes across primary studies included in the MASEM – There are two models that can be used as the basis for a MASEM analysis, the fixed-effects model and the random-effects model [27, 28]. These two models make different assumptions about the acceptable amount of variances across studies (i.e., heterogeneity of effect-sizes across studies), which lead to different definitions and calculations for the pooled effect-sizes [27, 28]. Under the fixed-effects model, it is assumed that there is one true population effect-size, which is shared by all the studies that are included in the MASEM analysis (i.e., the effect-sizes across studies are homogenous). It follows that the pooled effect-size is our estimate of this population effect-size and any variations across the studies are considered as sampling errors, which should be minimized if not removed using specific procedures. On the other hand, under the random-effects model, it is assumed that the true population effect-size could vary from study to study (i.e., the effect-sizes across studies are heterogeneous by nature) and the studies included in the MASEM are assumed to be a random sample of the population-level distribution of the effect-sizes. Under the random-effects model, the pooled effect-size estimates the mean of a distribution of effect-sizes [16]. Therefore, assessing and considering the amount of variances across studies is important for selecting the appropriate model for the MASEM analysis. Cheung and Chan [28] and Cheung [27] recommend that if the data drawn from the primary studies demonstrate heterogeneous effect-sizes, we should employ the random-effects model for the MASEM that uses the existing heterogeneity across the primary studies in weighting their correlations during the calculation of pooled effect-sizes. To that end, we assessed the level of between-study variances present in our data sets for both of our research models, using Cheung’s [26] proposed test of heterogeneity for MASEM analysis, in which we assessed the level of heterogeneity of the effect-sizes across studies using metaSEM package [25-27] in R 2.15.3 [110], as follows.

In assessing the heterogeneity of the effect-sizes, we drew on the SEM goodness of fit indices, as proposed by Cheung and Chan [28] and Cheung [26, 27], in which root mean square error of approximation (RMSEA) of 0.08 or less, and comparative fit index (CFI) and Tucker-Lewis Index (TLI) of 0.9 or above indicate homogeneous effect-sizes and any other values indicate heterogeneous effect-sizes across studies. Following Cheung and Chan [28] and Cheung
[26, 27], the fixed-effects model is justifiable only when there is an acceptable level of homogeneity across effect-sizes. Otherwise, random-effects model is the appropriate method for the MASEM analysis. The metaSEM results for the assessment of heterogeneity level demonstrate heterogeneous effect-sizes across the studies for both of our research models (i.e., research model 1: RMSEA=0.164, TLI=0.37, CFI=0.39; research model 2: RMSEA=0.151, TLI=0.19, CFI=0.21). This is further illustrated by $I^2$ heterogeneity index calculated for the pertinent correlation coefficients among the factors in our proposed research models 1 and 2, as reported in Appendix C, Tables C3a and C3b. $I^2$ heterogeneity index indicates the percentage of variance in a meta-analysis that is attributable to the heterogeneous effect-sizes (correlation coefficients) across the studies [54]. As a result, we used random-effects model as the basis for our MASEM analyses, as recommended in the literature [27, 28]. Furthermore, we retained the asymptotic covariance matrix (ACM) outputs that captured any heterogeneity that exists in our pooled correlation matrices based on the variance and covariance between effect-sizes reported in the primary studies [98]. The ACM enabled us to correct for the existing heterogeneity by weighting pooled correlations during evaluation of our research models (see appendix D for more detailed description).

3.2.3. Evaluation of the research models using SEM (stage two analysis)

Following two-stage random-effects MASEM procedures proposed by Cheung [26, 27], this step refers to the parameter estimation of the structural model using SEM and the meta-analytically pooled data from the primary studies. SEM computes fit indices (e.g., RMSEA) to evaluate the goodness-of-fit of our two research models. The objective of evaluating the goodness-of-fit is to reject a misspecified model and retain an acceptably specified and parsimonious model for interpretation [57], as follows.

In the two-stage random-effects MASEM, in addition to the matrix of pooled correlations, we use a weighting matrix, ACM. ACM is used to correct for the heterogeneity inherent in the pooled correlations and the differences in sample sizes for each pair in the pooled correlation matrix. The reason is that in practical reality not all primary studies measured all variables simultaneously [140]. Specifically, we used metaSEM package [25-27] to multiply each pair in the ACM by the total sample size of the studies that contributed correlations to each respective pair. This process is recommended by Cheung and Chan [28] and Cheung [27] to enable SEM to weight pairs in the pooled correlation matrix to correct for their heterogeneity (i.e., captured in the ACM) and the relative sample size of each pooled correlation. By assigning the aforementioned weight to each correlation, the researchers not only give each data point its proper amount of impact on the final parameter estimates [143], but also develop a covariance matrix to be used in the covariance-based SEM for testing the hypotheses in a research model [28].

To test the stated hypotheses in our proposed research models, following the two-stage random-effects MASEM approach by Cheung [26, 27], we implemented generally weighted least squares (GWLS – Also called asymptotically distribution-free (ADF) estimation [28]) estimation method in metaSEM package [25-27] in R 2.15.3 [110]. This enabled us to compute the goodness-of-fit statistics and the structural parameters of our research models using the pertinent meta-analytic data [98]. As recommended by Cheung and Chan [28] and Cheung [26, 27], we evaluated three complementary fit indices: the absolute fit index RMSEA, the relative fit index CFI, and the parsimonious fit index TLI. Values of the RMSEA 0.08 or less, CFI of at least 0.90, and TLI of at least 0.90 indicate very good model fit [57]. However, as reported by
Cheung and Chan [28], goodness-of-fit indices (e.g., TLI) resulted from GWLS (i.e., ADF) estimation method in covariance-based SEM analysis may not be as good as the goodness-of-fit indices (e.g., TLI) resulted from the covariance-based SEM analysis with maximum likelihood as the estimation method. Cheung and Chan [28] contend that this is simply due to using GWLS as the estimation method and does not necessarily indicate inferior fit of the research model.

4. Results

4.1. Test of the Research Model 1 for Pre-Adoption of the Online Banking

The results of the two-stage random-effects MASEM analysis of our structural model 1 with GWLS as the estimation method are presented in Fig. 4 and Table 2. The fit statistics show that our structural model 1 exhibits an acceptable fit to the pertinent meta-analytic data (i.e., RMSEA=0.032, with 90% confidence interval of (0.026, 0.038); CFI=0.94; TLI=0.87). Estimated path coefficients (i.e., estimated beta values) and their significance levels are presented for each path in Fig. 4 along with the $R^2$ for the five endogenous factors. Furthermore, estimated path coefficients, $p$-values, 95% confidence interval, $I^2$ heterogeneity index, the fail-safe $K$, and the level of statistical power for each hypothesis in our structural model 1 are presented in Table 2.

In line with TAM literature, our findings show that perceived usefulness of the online banking and perceived ease of use of the online banking are significant determinants of intention to use the online banking (H1: 0.39, $p<0.001$; H2: 0.15, $p<0.05$), and perceived ease of use of the online banking significantly affects perceived usefulness of the online banking (H3: 0.44, $p<0.001$). As hypothesized, we found trust in the online banking and trust in the physical bank to have significant direct effects on intention to use the online banking (H4: 0.30, $p<0.001$; H5: 0.39, $p<0.001$). Our results also support our hypotheses that structural assurances significantly affect trust in the online banking (H7: 0.41, $p<0.001$) and consumers’ propensity to trust significantly affects trust in the physical bank (H8: 0.28, $p<0.001$). However, our results did not support two postulated hypotheses H6 and H9: trust in the physical bank and consumers’ propensity to trust significantly affect trust in the physical bank (H6: 0.14, $p>0.05$; H9: 0.06, $p>0.05$). Furthermore, our analyses indicate that, as hypothesized, social influence has significant direct effects on perceived usefulness (H12: 0.30, $p<0.001$), trust in the online banking (H13: 0.26, $p<0.001$), and perceived ease of use (H14: 0.50, $p<0.001$), towards pre-adoption of the online banking.
Fig. 4. Structural model 1 (adoption of the online banking)

Note 1: \( N=7151; \) \( k=29; \) *\( p<0.05; \) **\( p<0.01; \) ***\( p<0.001; \) NS: not significant; NA: data not available.

Note 2: \( df=13; \) RMSEA=0.032, with confidence interval of (0.026, 0.038); CFI=0.94; TLI=0.87.
Table 2
Estimated $I^2$ heterogeneity index, the fail-safe K, the statistical power, path coefficient, p-value, and 95% confidence interval for each hypothesis in structural model 1 (adoption of the online banking)

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Estimated in the Stage One of Two-Stage Random-Effects MASEM</th>
<th>Estimated in the Stage Two of Two-Stage Random-Effects MASEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I^2$ Heterogeneity Index Fail-Safe K Statistical Power</td>
<td>Estimated Path Coefficient P-Value 95% Confidence Interval</td>
</tr>
<tr>
<td>H1</td>
<td>0.924 191 &gt;0.95</td>
<td>0.39 &lt; 0.001 (0.26, 0.53)</td>
</tr>
<tr>
<td>H2</td>
<td>0.926 159 &gt;0.95</td>
<td>0.15 0.039 (0.01, 0.29)</td>
</tr>
<tr>
<td>H3</td>
<td>0.948 217 &gt;0.95</td>
<td>0.44 &lt; 0.001 (0.33, 0.54)</td>
</tr>
<tr>
<td>H4</td>
<td>0.919 50 &gt;0.95</td>
<td>0.30 &lt; 0.001 (0.15, 0.44)</td>
</tr>
<tr>
<td>H5</td>
<td>0.851 50 &gt;0.95</td>
<td>0.39 &lt; 0.001 (0.26, 0.53)</td>
</tr>
<tr>
<td>H6</td>
<td>0.868 16 &gt;0.95</td>
<td>0.14 0.194 (-0.07, 0.35)</td>
</tr>
<tr>
<td>H7</td>
<td>0.868 58 &gt;0.95</td>
<td>0.41 &lt; 0.001 (0.25, 0.57)</td>
</tr>
<tr>
<td>H8</td>
<td>0.000 6 &gt;0.95</td>
<td>0.28 &lt; 0.001 (0.21, 0.34)</td>
</tr>
<tr>
<td>H9</td>
<td>0.000 9 &gt;0.95</td>
<td>0.06 1.497 (-0.24, 0.37)</td>
</tr>
<tr>
<td>H12</td>
<td>0.223 55 &gt;0.95</td>
<td>0.30 &lt; 0.001 (0.22, 0.37)</td>
</tr>
<tr>
<td>H13</td>
<td>0.231 25 &gt;0.95</td>
<td>0.26 0.005 (0.08, 0.44)</td>
</tr>
<tr>
<td>H14</td>
<td>0.767 52 &gt;0.95</td>
<td>0.50 &lt; 0.001 (0.43, 0.57)</td>
</tr>
</tbody>
</table>

4.2. Test of the Research Model 2 for Post-Adoption of the Online Banking

The results of the two-stage random-effects MASEM analysis of our structural model 2 with GWLS as the estimation method are presented in Fig. 5 and Table 3. The results show that our structural model 2 exhibits acceptable fit to the meta-analytic data (i.e., RMSEA=0.029, with 90% confidence interval of (0.026, 0.033); CFI=0.96; TLI=0.89). Path coefficients and their significance levels are presented for each path in Fig. 5 along with the $R^2$ for the four endogenous variables. Furthermore, estimated path coefficients, p-values, 95% confidence interval, $I^2$ heterogeneity index, the fail-safe K, and the level of statistical power for each hypothesis in our structural model 2 are presented in Table 3.

In line with our hypotheses, our findings show that perceived usefulness of the online banking is a significant determinant of the continued use intention of the online banking (H15: 0.41, p<0.001). Our analyses show that perceived ease of use has no significant direct effect on the post-adoptive continued use intention of the online banking (H16: 0.11, p>0.05), although it significantly affects perceived usefulness (H17: 0.52, p<0.001). As hypothesized, we also found that trust in the online banking and trust in the physical bank have significant direct effects on the post-adoptive continued use intention (H18: 0.24, p<0.01; H19: 0.40, p<0.001). Our results also show that trust in the physical bank and structural assurances significantly affect trust in the online banking (H20: 0.26, p<0.05; H21: 0.22, p<0.01). Furthermore, as expected, system quality significantly affects perceived ease of use (H29: 0.53, p<0.001). Our results also indicate that information quality significantly affects perceived usefulness (H30: 0.31, p<0.001) and trust in the online banking (H31: 0.26, p<0.01). Moreover, we found that service quality is a significant antecedent of perceived ease of use (H32: 0.37, p<0.001) and trust in the online banking (H34:
0.30, p<0.05). However, it has no significant direct effect on perceived usefulness (H33: 0.09, p>0.05). Finally, our analyses show that social influence has no significant direct effects on perceived usefulness (H24: 0.08, p>0.05), trust in the online banking (H25: 0.10, p>0.05), and perceived ease of use (H26: 0.07, p>0.05), towards post-adoption of the online banking.

Note 1: N=18114; k=52; *p<0.05; **p<0.01; ***p<0.001; NS: not significant; NA: data not available.
Note 2: df=14; RMSEA=0.029, with confidence interval of (0.026, 0.033); CFI=0.96; TLI=0.89.

**Fig. 5.** Structural model 2 (continued use of the online banking)
Table 3
Estimated $I^2$ heterogeneity index, the fail-safe $K$, the statistical power, path coefficient, p-value, and 95% confidence interval for each hypothesis in structural model 2 (continued use of the online banking)

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Estimated in the Stage One of the Two-Stage Random-Effects MASEM</th>
<th>Estimated in the Stage Two of the Two-Stage Random-Effects MASEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I^2$ Heterogeneity Index Fail-Safe $K$ Statistical Power</td>
<td>Estimated Path Coefficient P-Value 95% Confidence Interval for Estimated Path Coefficient</td>
</tr>
<tr>
<td>H15</td>
<td>0.915 132 &gt;0.95</td>
<td>0.41 &lt; 0.001 (0.24, 0.59)</td>
</tr>
<tr>
<td>H16</td>
<td>0.844 113 &gt;0.95</td>
<td>0.11 0.395 (-0.14, 0.35)</td>
</tr>
<tr>
<td>H17</td>
<td>0.912 215 &gt;0.95</td>
<td>0.52 &lt; 0.001 (0.42, 0.62)</td>
</tr>
<tr>
<td>H18</td>
<td>0.824 91 &gt;0.95</td>
<td>0.24 0.005 (0.07, 0.40)</td>
</tr>
<tr>
<td>H19</td>
<td>0.570 26 &gt;0.95</td>
<td>0.40 &lt; 0.001 (0.23, 0.58)</td>
</tr>
<tr>
<td>H20</td>
<td>0.936 56 &gt;0.95</td>
<td>0.26 0.020 (0.04, 0.48)</td>
</tr>
<tr>
<td>H21</td>
<td>0.955 121 &gt;0.95</td>
<td>0.22 0.001 (0.09, 0.34)</td>
</tr>
<tr>
<td>H24</td>
<td>0.795 44 &gt;0.95</td>
<td>0.08 0.134 (-0.02, 0.19)</td>
</tr>
<tr>
<td>H25</td>
<td>0.940 28 &gt;0.95</td>
<td>0.10 0.190 (-0.05, 0.25)</td>
</tr>
<tr>
<td>H26</td>
<td>0.853 32 &gt;0.95</td>
<td>0.07 0.280 (-0.06, 0.21)</td>
</tr>
<tr>
<td>H29</td>
<td>0.853 55 &gt;0.95</td>
<td>0.53 &lt; 0.001 (0.42, 0.64)</td>
</tr>
<tr>
<td>H30</td>
<td>0.812 69 &gt;0.95</td>
<td>0.31 &lt; 0.001 (0.24, 0.59)</td>
</tr>
<tr>
<td>H31</td>
<td>0.004 44 &gt;0.95</td>
<td>0.26 0.008 (0.07, 0.45)</td>
</tr>
<tr>
<td>H32</td>
<td>0.676 81 &gt;0.95</td>
<td>0.37 &lt; 0.001 (0.27, 0.48)</td>
</tr>
<tr>
<td>H33</td>
<td>0.812 33 &gt;0.95</td>
<td>0.09 0.624 (-0.23, 0.41)</td>
</tr>
<tr>
<td>H34</td>
<td>0.000 10 &gt;0.95</td>
<td>0.30 0.014 (0.07, 0.54)</td>
</tr>
</tbody>
</table>

Our structural models 1 and 2, depicted in Fig. 4 and 5, represent meta-analytic models of the relationships between the factors that affect consumers’ pre- and post-adoption of the online banking. Nonetheless, it is plausible that alternative models could predict and explain consumers’ adoption of the online banking in different manners and with different explanatory powers (i.e., $R^2$). Therefore, to assess the explanatory power of our structural models, consistent with the SEM literature (e.g., [72]), we examined the possible alternative models. To that end, path coefficients and explanatory powers ($R^2$) were estimated for a set of five nested alternative models (i.e., two nested alternative models based on our structural model 1 and three nested alternative models based on our structural model 2), as presented in Appendix E. The results of alternative model testing demonstrate that our structural models are superior to the five nested alternative models.

4.3. Total Effects of Factors Affecting Intention to Use and Continued Use Intention of the Online Banking

Bollen Kenneth [15] stresses that it is important to consider not only the significant direct effects (i.e., indicated by path coefficients in our structural models, depicted in Fig. 4 and Fig. 5), but also the total effects in interpreting results in a SEM [15]. Total effects show the combined effect of any direct path from a given factor (e.g., trust in the physical bank) to our dependent factor (e.g., continued use intention of the online banking), as well as any indirect effects transmitted through other intervening factors [7]. The indirect effect of a factor is calculated by
the product of the path coefficients along an indirect route from that factor to the dependent factor via tracing arrows in the headed direction only [7]. For example, in our structural model 2 (Fig. 5), trust in the physical bank has a significant direct effect on continued use intention of the online banking (0.40), as well as an indirect effect through trust in the online banking (0.26 × 0.24 = 0.06). The combination of these two effects is reflected in the total effect of trust in the physical bank on continued use intention of the online banking (0.40 + 0.06 = 0.46), which means that one standard deviation increase in trust in the physical bank results in 0.46 standard deviation increase in continued use intention of the online banking, at the post-adoption stage. Tables 4 and 5 present the total effects along with their 95% confidence intervals for each of the factors shown in our structural models in Fig. 4 and 5, respectively.
## Table 4
Total effects of each of the factors in our Structural model 1, Fig. 4, on Intention to Use the Online Banking

<table>
<thead>
<tr>
<th>Factors</th>
<th>Estimated Direct Effect</th>
<th>95% Confidence Interval</th>
<th>Estimated Indirect Effect</th>
<th>95% Confidence Interval</th>
<th>Estimated Total Effect</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust in the Physical Bank</td>
<td>0.39</td>
<td>(0.26, 0.53)</td>
<td></td>
<td></td>
<td>0.39</td>
<td>(0.26, 0.53)</td>
</tr>
<tr>
<td>Perceived Usefulness of the Online banking</td>
<td>0.39</td>
<td>(0.26, 0.53)</td>
<td></td>
<td></td>
<td>0.39</td>
<td>(0.26, 0.53)</td>
</tr>
<tr>
<td>Social Influence</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.36</td>
<td>(0.11, 0.72)</td>
</tr>
<tr>
<td>Perceived Ease of Use of the Online banking</td>
<td>0.15</td>
<td>(0.01, 0.29)</td>
<td>0.06</td>
<td>(0.003, 0.19)</td>
<td>0.46</td>
<td>(0.23, 0.77)</td>
</tr>
<tr>
<td>Trust in the Online Banking</td>
<td>0.30</td>
<td>(0.15, 0.45)</td>
<td></td>
<td></td>
<td>0.32</td>
<td>(0.10, 0.57)</td>
</tr>
<tr>
<td>Structural Assurances</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.12</td>
<td>(0.04, 0.25)</td>
</tr>
<tr>
<td>Consumers’ Propensity to Trust</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.11</td>
<td>(0.05, 0.18)</td>
</tr>
</tbody>
</table>

* Based on Preacher and Kelley’s [107] guidelines the estimated direct and indirect coefficients computed from our MASEM model are based on standardized beta-values.

## Table 5
Total effects of each of the factors in our structural model 2, Fig. 5, on Continued Intention of the Online Banking

<table>
<thead>
<tr>
<th>Factors</th>
<th>Estimated Direct Effect</th>
<th>95% Confidence Interval</th>
<th>Estimated Indirect Effect</th>
<th>95% Confidence Interval</th>
<th>Estimated Total Effect</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust in the Physical Bank</td>
<td>0.40</td>
<td>(0.23, 0.58)</td>
<td></td>
<td></td>
<td>0.46</td>
<td>(0.23, 0.77)</td>
</tr>
<tr>
<td>Perceived Usefulness of the Online banking</td>
<td>0.41</td>
<td>(0.24, 0.59)</td>
<td></td>
<td></td>
<td>0.41</td>
<td>(0.24, 0.59)</td>
</tr>
<tr>
<td>Trust in the Online Banking</td>
<td>0.24</td>
<td>(0.07, 0.40)</td>
<td></td>
<td></td>
<td>0.27</td>
<td>(0.07, 0.40)</td>
</tr>
<tr>
<td>Perceived Ease of Use of the Online banking</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.21</td>
<td>(0.10, 0.37)</td>
</tr>
<tr>
<td>Information Quality</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.19</td>
<td>(0.05, 0.43)</td>
</tr>
<tr>
<td>Service Quality</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.15</td>
<td>(0.03, 0.39)</td>
</tr>
<tr>
<td>System Quality</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.11</td>
<td>(0.04, 0.23)</td>
</tr>
<tr>
<td>Structural Assurances</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>0.05</td>
<td>(0.01, 0.14)</td>
</tr>
<tr>
<td>Social Influence</td>
<td>–</td>
<td>–</td>
<td></td>
<td></td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

* Based on Preacher and Kelley’s [107] guidelines the estimated direct and indirect coefficients computed from our MASEM model are based on standardized beta-values.
5. Discussions and Implications

This study brings conceptual and empirical clarity to the factors affecting online banking adoption based on the systematic review of the online banking adoption literature and the MASEM analysis of two structural models pertaining to pre- and post-adoption of the online banking. Our study makes three major contributions to theory, as follows.

First, our findings demonstrate that there is a distinction between the factors and their nomological relationships for pre- and post-adoption of the online banking, as depicted in Fig. 4 and Fig. 5. A major distinction between our two structural models is the significance of system quality, information quality, and service quality on the post-adoption of the online banking. These factors are based on consumers' direct experience with the online banking system [14].

Our findings, depicted in Table 5, demonstrate the relative importance of these factors towards the post-adoption of the online banking. This is consistent with Xu et al. [144] discussions based on schema theory. Schema theory [91, 115] posits that individuals construct various schemata based on their prior knowledge or experience with different objects, such as online systems [144]. Furthermore, extant literature (e.g., [14, 68, 92, 133]) contends that systems quality, information quality, and service quality determine the schemata that consumers rely on towards adopting an online system. Our findings confirm the significance of these factors and nomologically clarify their effects on consumers’ post-adoption of the online banking. As a case in point, our findings show that information quality has larger total effect on consumers’ perceived usefulness of the online banking system (i.e., 0.31), as compared to system quality (i.e., 0.27). To that end, our findings corroborate the contentions in the technology adoption literature that higher level of system quality reduces the effort that consumers should expend to learn and use the system, thus, makes the system more useful for the consumers [116]. In other words, system quality indirectly increases the usefulness of an online banking system for consumers by improving its ease of use. In contrast, our findings show that information quality directly increases the usefulness of the online banking system for the consumers. This is because online consumers process the content of the online banking system – information – to conduct their transactions and make financial decisions. Therefore, higher quality of information in an online banking system makes it more useful for consumers towards fulfilling their transactional and financial decision-making needs.

Second, this paper contributes to the systematic literature review and meta-analysis research in the Information Systems, in particular technology adoption literature. Scholars have called for meta-analysis researches in the Information Systems [95, 127] because they believe that the meta-analysis methodology is under-utilized to assess the nature of inconsistent quantitative empirical findings on essentially the same research questions. To this end, our study combines the Grounded Theory Literature Review and two-stage random-effects MASEM methods to identify and meta-analytically clarify the significance of factors that affect consumers’ pre- and post-adoption of the online banking. For instance, prior meta-analytic studies (e.g., [154]) provide support for the significance of social influence in technology adoption. Our results adds to their contribution by demonstrating that this effect is significantly stronger in the pre-adoption stage, as compared to the post-adoption stage. Moreover, our results depicted in Tables 4 and 5, show that trust in the physical bank has more effects than perceived usefulness on consumers’ pre- and post-adoption intention.

Third, we show that seven hypotheses that were based on the extant literature cannot be supported, when assessed simultaneously with the other factors in our structural models. Possible
justifications are as follows. Our structural model 1 (Fig. 4) shows that **structural assurances** is the only significant antecedent of trust in the online banking, while **trust in the physical bank** and **consumers’ propensity to trust** have no significant effects on it (i.e., H6, H9 not supported). Our conjecture is that this could be due to the prominence of structural assurances in the online banking at the pre-adoption stage. Therefore, it is possible that the structural assurances absorb most of the variance in the trust in the online banking, which otherwise could have been explained by the trust in the physical bank and consumers’ propensity to trust. Furthermore, structural model 2 (Fig. 5) shows that five hypotheses (H16, H24, H25, H26, H33) were not supported, when assessed simultaneously with the other factors in the model. In regard to the insignificant effects of **social influence** (H24, H25, H26), extant literature (e.g., [64, 137, 139]) contend that due to continued use experience at the post-adoption stage of the system usage, some of the experiential factors (e.g., system quality, information quality, and service quality) gain prominence, while social influence loses significance in influencing consumers’ continued use intention. In regard to insignificant direct effect of **perceived ease of use** (H16) on continued use intention, research findings (e.g., [139]) show that effort-oriented constructs (e.g., perceived ease of use) are more salient in the pre-adoption stage of the innovation adoption. The reason is that, ease of use plays an important role at the early stages of usage when complexity of the new systems represents initial hurdles that need to be overcome by the consumers. However, the significance of ease of use on the intention in the post-adoption stage is overshadowed by other factors [139] (e.g., trust in the online banking and perceived usefulness of the online banking), as consumers gain experience with the system. In regard to the insignificant effect of **service quality** on perceived usefulness (H33), there is evidence that service quality is highly correlated with the information quality and system quality [144, 146]. Our conjecture is that, in our structural model 2, information quality and system quality explain the variance in the perceived usefulness that otherwise would have been explained by the service quality. Nonetheless, these conjectures provide important venues for future research to test and verify them.

Our study also has implications for practice. Retail banks must make special attention to inform/educate the consumers about the usefulness of their online banking products as well as the safety and trustworthiness of their physical and online banking channels to garner consumer trust. This would suggest that investing in other factors might be less effective in the absence of primary attention to the trust in the physical and the online banking channels as well as usefulness of the online banking channels. It is quite possible that the low adoption of the online banking, as noted in our Introduction section, can be attributed to the lack of attention by the banking sector to inform/educate the consumers about the nature of the pertinent factors (depicted in Table 4) affecting pre-adoption of the online banking. The merit of this conjecture can be gleaned from a recent investigation by Xue et al. [145] that found consumers who live in areas with a high branch density or high online banking penetration increase their product acquisition and transaction activity more than online banking adopters in other regions. Banks routinely use customer demographics to segment their customer base and target product promotions. Therefore, it is possible that specific consumer segments are intentionally/unintentionally disenfranchised because of poor outreach of physical banks to inform/educate them about the factors depicted in Table 4. This conjecture needs to be assessed in the future studies.
6. Limitations

Notwithstanding the contributions of our study, it has two limitations. Firstly, due to the lack of sufficient data, we were unable to test the effects of “consumers’ innovativeness” in the pre-adoption stage and “consumers’ innovativeness” and “propensity to trust” in the post-adoption stage. Despite the importance of these factors in the diffusion of innovations literature [2, 92, 152], there is a paucity of empirical studies assessing their significance towards adoption of the online banking, which needs to be addressed in the future research. Secondly, despite their conceptual similarity, the measures provided for each factor in different empirical studies can vary. For example, online banking system quality has been measured in the literature in terms of reliability [50], accessibility [73], speed [49, 149, 156], flexibility [73], aesthetics [47, 156], and navigation [47, 131, 156]. Different online banking studies have used different subsets of these attributes for measuring system quality. Since the measurement can be a moderator of the relationship between factors, a potential downside of merging these measures is increased heterogeneity in the meta-analytic data. Nevertheless, as noted in the methodology section, an important benefit of using multiple measures for a given factor is higher content validity of the factors in the meta-analysis, as compared to the primary studies. By merging multiple conceptually similar measures, we are capturing not just one aspect of a factor (such as the reliability for system quality), but also a comprehensive set of aspects of the factor [105].

7. Conclusions

For more than a decade, researches on the online banking adoption have investigated different factors of researchers’ individual interests without a systematic integration among them. At the same time, we observe findings that are inconsistent or even contradict one another across different studies, which make it difficult to draw meaningful conclusions from the literature. In order to ameliorate these problems, this study draws on a theory-driven systematic review of the online banking adoption literature, using Grounded Theory Literature Review and two-stage random-effects MASEM methods, to delineate the factors affecting pre- and post-adoption of the online banking. To that end, we use the innovation diffusion theory as the theoretical foundation to propose and statistically test two structural models. Our first structural model, which illustrates the factors and their nomological relationships towards pre-adoption of the online banking, has been statistically validated based on the meta-analytical data collected from 29 primary empirical studies examining 7,151 cases of pre-adoption of the online banking. Likewise, our second structural model, which illustrates the factors and their nomological relationships affecting post-adoption of the online banking, has been statistically validated based on meta-analytical data collected from 52 primary empirical studies providing 18,114 cases of post-adoption of the online banking. Our findings contribute to the online banking adoption literature by bringing conceptual and empirical clarity to the factors affecting online banking adoption and illustrating the distinction between them as well as their nomological relationships based on the stage of the online banking adoption (i.e., pre- and post-adoption of the online banking). Furthermore, our study demonstrates the factors drawn from the extant online banking adoption literature that do not affect the pre- or post-adoption of the online banking, when assessed simultaneously with the other factors in one structural model. This finding along with the total effect of each factor on the pre- and post-adoption of the online banking provide a sound basis for determining the relative importance of each factor towards the online banking adoption.
at different stages of the adoption. Overall, our findings have insightful implications for the practitioners, such as banks, by shedding light on the areas to which they should make special attention in order to promote the consumers’ pre- and post-adoption of their online banking systems.

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1. References marked with an asterisk (*) denote studies that supplied data for our analysis.


