Does it take a pandemic for digitalization to thrive?

An analysis of telemedicine adoption in Swiss healthcare organizations in the context of the COVID-19 pandemic

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Foreword

This study was written to complete a master's degree program in Public Management and Policy at the University of Bern, Switzerland. This curriculum focuses on the increasing complexity of the state's functions and its forms of intervention, requiring a new understanding of public service in general and the modernization of public administrations. This study considers telemedicine adoption in Swiss healthcare organizations during the COVID-19 pandemic that falls within the scope of this program, as it provides new insights into the broader subjects of digital health and eHealth, which have been of great concern to Swiss decision-makers in the healthcare sector over the past years and even more so today, with a global pandemic still underway.

I would like to thank Professor Rudolf Blankart for the enthusiasm and support shown in the subject matter of my choice and for his availability and patience in proactively answering my questions and doubts.

I would also like to thank my colleagues for their flexibility and support during the writing of this thesis. They never hesitated to respect my time dedicated to this study's writing and to bring their ideas and input during the writing process. I would especially thank Mrs. Petra Wessalowski and Mr. Willi Brand for acting as intermediaries at the healthcare organizations that were this study's subjects. They greatly participated in and encouraged this study.

I would also like to thank all the physicians who participated in my survey, especially given the difficult period for healthcare personnel. I am profoundly grateful to those who supported me in answering the questionnaire and for the valuable feedback I received.

Finally, I would like to thank my entire entourage, family, and friends, who shared approaches and ideas with me and thus provided new ideas and solutions throughout the research process.

Executive Summary

With the COVID-19 pandemic outburst, several authors have reported an increased use of telemedicine in healthcare organizations (i.a. Golinelli et al., 2020; Jazieh & Kozklakidis, 2020; Loeb et al., 2020; Robinson et al., 2020; Tebeje & Klein, 2020). In Switzerland, a similar trend has been observed for telemedicine utilization, especially boosting the area of remote health consultation (KPMG, 2020, p. 16). However, despite these remarkable increases, telemedicine utilization in Switzerland has been lagging behind in international comparison (Thiel et al., 2018, p. 225). Digitalization in the healthcare sector is subject to various structural, organizational, and institutional barriers firmly embedded in healthcare systems, thus resulting in fragmentation and silo thinking (OECD, 2019, p. 32). In a post-COVID-19 era, where a substantial portion of healthcare services will likely remain largely digital-based, it is therefore crucial to identify the factors influencing technology adoption decisions to ensure that healthcare organizations can move beyond crisis mitigation, favoring clearer and more targeted planning of telemedicine utilization. This study aimed to identify the factors impacting organizational telemedicine adoption decisions in Swiss healthcare organizations regarding COVID-19. Consequently, new insights into the area of organizational technology adoption were provided alongside hands-on information for healthcare organizations' decision-makers to develop appropriate support for managing telemedicine technology properly.

Approach and Method

To identify the factors predicting organizational telemedicine adoption, this study relied on the findings of P. J.-H. Hu et al. (2002) in their exploratory study of telemedicine adoption in Hong Kong healthcare organizations. The authors identified six factors as contributors to targeted technology adoption: perceived service benefits (PSB), perceived service risks (PSR), perceived service needs (PSN), collective attitude of medical staff (CAM), perceived ease of use (PEOU), and perceived technology safety (PTS). This pre-identified structure was tested in this study using confirmatory factor analysis, and the effects of these factors on adoption were then analyzed using a path analysis. First, prior knowledge on the structure underlying latent variables was required, and the hypothesized structure of the measurement model was tested statistically via CFA, based on knowledge of the theory or prior empirical research. Once CFA was performed, hypotheses on the relationship between the dependent and independent variables were formulated and tested using path analysis. To test the hypothesis, data were collected from Swiss healthcare organizations through an online questionnaire between December 2020 and February 2021, resulting in a sample of 77 hospitals.

Results and Conclusion

This study's findings provided some interesting insights into the factors driving organizational telemedicine adoption in Swiss healthcare organizations, although some of the results were statistically non-significant. Similar to P. J.-H. Hu et al. (2002), PEOU significantly negatively affected telemedicine adoption, suggesting that the more advanced an organization is in adopting telemedicine, the less PEOU plays a role in it. This result suggests a close link to users' experience and individual's general beliefs on technology and technology use. PSB significantly positively affected telemedicine adoption, revealing a better knowledge of telemedicine today than in the past, which proves the benefits of telemedicine, especially to medical and health-related issues. Despite its limitations, this study generated new insights into a topic that has now regained importance following the COVID-19 pandemic, providing practical and pragmatic understandings of telemedicine adoption and hence calling for further research on this issue.

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1. INTRODUCTION

1.1 Context and problem definition

On February 25, 2020, Switzerland was hit by the first coronavirus case and has been among the countries with the highest number of COVID-19 cases per capita in the world (Salathé et al., 2020, p. 1). With the urgency of reducing exposure to the virus while allowing patients and health professionals to interact and coordinate, an increasingly widespread application of electronic health (eHealth) solutions has been observed (Tebeje & Klein, 2020, p. 1). Among these solutions, telehealth services, such as telemedicine, were widely employed as an effective tool to tackle the challenges of the pandemic (Jahns et al., 2020, n.p.). Telehealth refers to using a tool in managing long-term conditions in the community to proactively monitor vital signs of patients and rapidly respond in case of complications (Stowe & Harding, 2010, p. 195), therefore assuming a character of public health (Denz, 2003, p. 2). Telemedicine, instead, encompasses the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or pictures, to the actual treatment, health education, and transfer of medical data (Stowe & Harding, 2010, p.196; Angerer et al., 2017, p. 11). In managing communicable diseases such as COVID-19, distance consultation is a key factor in slowing down virus transmission to avoid person-to-person contact (Smith et al., 2020, p. 309). As telemedicine has proven to be successful during previous acute respiratory infectious diseases, such as severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), it has been extensively used in addressing COVID-19 (Hoseini & Zare, 2020, p. 66). This is also true for Switzerland: several authors reported how the COVID-19 pandemic boosted telemedicine, especially for remote health consultation (i.a., Jaun & Wagner, 2020, n.p.; Wagner, 2020, n.p.).

Before the COVID-19 pandemic, however, telemedicine in Switzerland was lagging behind in international comparison: in 2018, Switzerland was ranked in the fourth last place for digital innovation (Thiel et al., 2018, p. 225). Moreover, the annual Swiss eHealth barometer, which has been annually investigating the current status and development of eHealth in Switzerland since 2009, showed that Swiss telemedicine utilization had hardly changed in percentage since 2014 and was only used in limited cases to provide medical services for patients, mostly among hospitals and practice physicians (gfs. Bern, 2020, p. 27). As of today, numerous authors have specified that the COVID-19 pandemic acted as an accelerator for the transition of healthcare organizations to virtual care (i.a. Golinelli et al., 2020; Jazieh & Kozklakidis, 2020; Loeb et al., 2020; Robinson et al., 2020; Tebeje & Klein, 2020). Furthermore, in the post-COVID-19 era, it is likely that a substantial portion of healthcare services will remain largely digital-based, as they have been recognized as more suitable in addressing the healthcare system flow rate and capacity challenges and in providing better patient-centered care (Jazieh & Kozlakidis, 2020, p. 2). Nonetheless, despite recent evidence suggesting telemedicine's success and its change in use by healthcare organizations, its durability is lacking in the current literature. The disposition to fully adopt telemedical services will largely depend on overcoming the hurdles that healthcare organizations face in spite of COVID-19 (Nittas & Von Wyl, 2020, p. 2). Also, although the use of general eHealth solutions in Swiss hospital settings is more advanced than in general practitioner's settings, considerable variation exists among hospitals and cantons (De Pietro et al., 2015, p. 133). By identifying the factors impacting organizational technology adoption, healthcare organizations can ensure that digital solutions—telemedicine in particular—will move beyond mere containment and crisis mitigation, favoring clearer and more targeted planning of telemedicine usage. Understanding the fundamentals underlying the adoption process is therefore crucial and can provide the needed information for healthcare organizations' decision-makers to develop appropriate decision support for better management of telemedicine technology.

1.2 Objectives and research question

In their previous exploratory study of telemedicine adoption by healthcare organizations in Hong Kong, P. J.-H. Hu et al. (2002) identified six factors as contributors to targeted technology adoption: perceived service benefits (PSB), perceived service risks (PSR), perceived service needs (PSN), collective attitude of medical staff (CAM), perceived ease of use (PEOU), and perceived technology safety (PTS), with CAM and PSR being significant determinants of targeted technology adoption. The application of this identified structure to new data samples and different contexts (the Swiss one) allows for new insights into and management implications for the Swiss healthcare sector. This study's purpose is therefore twofold. First, this study cross-validated the relationship between the factor structure and the scale developed by P. J.-H. Hu et al. (2002) using a confirmatory factor analysis (CFA) on a new sample. To do so, the first preliminary research question was formulated:

RQ1: *Do the hypothesized six-factor structures by P. J.-H. Hu et al. (2002) adequately fit with the sample data?*

Second, this study assessed whether these factors determined organizational technology adoption decisions in Swiss healthcare organizations in the context of the COVID-19 crisis. To do so, a factor score path analysis was conducted. Although the data available for this analysis did not allow to directly investigate the role of the pandemic itself in adopting telemedicine, it is fair to assume that the context posed by this extraordinary situation greatly impacted the importance of this technology in healthcare organizations (Jahns et al., 2020, n.p.). Therefore, the following research question was developed:

RQ2: *How do the six factors PSB, PSR, PSN, CAM, PEOU, and PTS predict telemedicine technology adoption in Swiss healthcare organizations during the COVID-19 pandemic?*

1.3 Structure of the paper

The next chapters are structured as follows: Chapter 2 overviews the Swiss healthcare system and describes digitalization in the Swiss healthcare sector. It also outlines the specifics of the telemedicine technology. Chapter 3 defines the theoretical background and provides a literature review of organizational technology adoption. Chapter 4 briefly explains the rationale behind the undertaken analysis to clarify the research hypotheses, methods, model estimation, and analysis that follow in Chapters 5 and 6, respectively. Chapter 7 discusses the findings and limitations. Finally, Chapter 8 concludes the study and presents an outlook on further research opportunities.

2. SETTING THE CONTEXT: DIGITALIZATION IN THE SWISS HEALTHCARE SECTOR AND THE COVID-19 PANDEMIC

2.1 Premise: A short overview of the Swiss healthcare system

Given Switzerland's federal nature, duties and responsibilities concerning the healthcare system are divided among the federal, cantonal, and communal levels of government (Camenzind, 2016, p. 161). While the federal structure is decentralized for financing, organizing, and providing healthcare, market-based and politically controlled elements influence the areas of health insurance, healthcare provision, and the production and distribution of healthcare products (De Pietro et al., 2015, p. 255). At the federal level, the Federal Health Insurance Act (KVG/LAMal) defines the competences of the Confederation, which holds responsibility for financing the health system, premium and tariff design, quality assurance, and cost containment (Sax, 2008, p. 5). Since 1996, mandatory health insurance regulated under the Federal Health Insurance Act (KVG/LAMal) must be purchased by all Swiss residents: competing private health insurance companies are compelled to accept anyone who intends to obtain an insurance but cannot, however, profit from the mandatory insurance activities (De Pietro et al., 2015, p. 21). This compulsory basic insurance covers a catalog of government-defined services and is mainly financed by per-capita premiums offered by insurers (Sax, 2008, p. 2). Premiums vary within geographically defined "premium regions" according to the age group (< 19; 19–25; <25), the level of chosen annual deductible, and for specific insurance plans (Camenzind, 2016, p. 162). Other than mandatory health insurance premiums, sources of publicly financed health insurance stem from tax-financed budgets at the national, cantonal, and communal levels, alongside social insurance contributions from health-related coverage of accident, old-age, disability, and military insurances (Camenzind, 2016, p. 161). Beyond mandatory health insurance, free competition applies to additional services that are not covered by basic insurance (Camenzind, 2016, p. 162) and treatments in the area of complementary medicine, choice of hospital, hospitality facilities, or choice of doctor within the hospital (Sax, 2008, p. 3). Although this complementary health insurance coverage is voluntary (Camenzind, 2016, p. 162), a significant proportion of health services are paid out of the pocket (Sax, 2008, p. 3). Patients are generally free to choose their own doctor and the hospital in which they wish to undergo treatment—a key characteristic of the Swiss healthcare system (De Pietro et al., 2015, p. 161)—unless they opted for an insurance model that includes a restriction (Sax, 2008, p. 3), so-called managed care plans. Cantons handle matters that are not specifically designated by the federal constitution to be handled by the Confederation (Camenzind, 2016, p. 161). Therefore, 26 entities control the planning, operation, and financial security of the inpatient sector; supervise professional licenses and practice permits; manage universities and universities of applied sciences; secure healthcare provision to their population; deliver and apply various health-related legislation; and they provide subsidies to low-income households and direct prevention and health promotion activities (Sax, 2008, p. 6; De Pietro et al., 2015, p. 19). At the communal level, the role of municipalities in the healthcare sector varies and rests on decisions within each canton (De Pietro et al., 2015, p. 20). Communes mostly handle the area of long-term care (nursing homes and homecare services) or other services involving social support for vulnerable groups; their engagement may vary according to their size, where larger municipalities generally take on more responsibilities than smaller ones, which might, in turn, combine or delegate specific tasks to private organizations to meet their obligations (De Pietro et al., 2015, p. 29). Corporatist bodies representing civil society, mandatory health insurance companies and their institutions, providers, associations, and citizens are also important stakeholders involved in the decision-making process (De Pietro et al., 2015, p. 19).

Outpatient care is delivered mostly by self-employed physicians working in independent, single practices, offering both primary and specialized care (De Pietro et al., 2015, p. 155). Inpatient care is provided by acute care hospitals, which increasingly play an important role in the provision of ambulatory and daycare services (De Pietro et al., 2015, p. 155). Public and private hospitals coexist, and those included on hospital lists drawn up by cantons can provide services reimbursable by mandatory health insurance (Sax, 2008, p. 3). Since the implementation of the hospital financing reform in 2012, patients can basically freely choose the hospital in which they wish to undergo treatment once the elected hospital is included on the cantonal hospital list; however, reimbursement follows the rules of the patient’s canton of residence, which means that it is limited to the level of expenses that would have incurred if the patient had been treated in his canton of residence (De Pietro et al., 2015, pp. 155–156). Cantons account for about 55% of the costs of each inpatient admission, and the rest is paid by insurers (De Pietro et al., 2015, p. 118). A national diagnosis-related group (DRG) pays for services covered by mandatory health insurance (Camenzind, 2016, p. 164). Figure 1 overviews the different stakeholders that constitute the complex Swiss healthcare system and the relationships that exist among them.

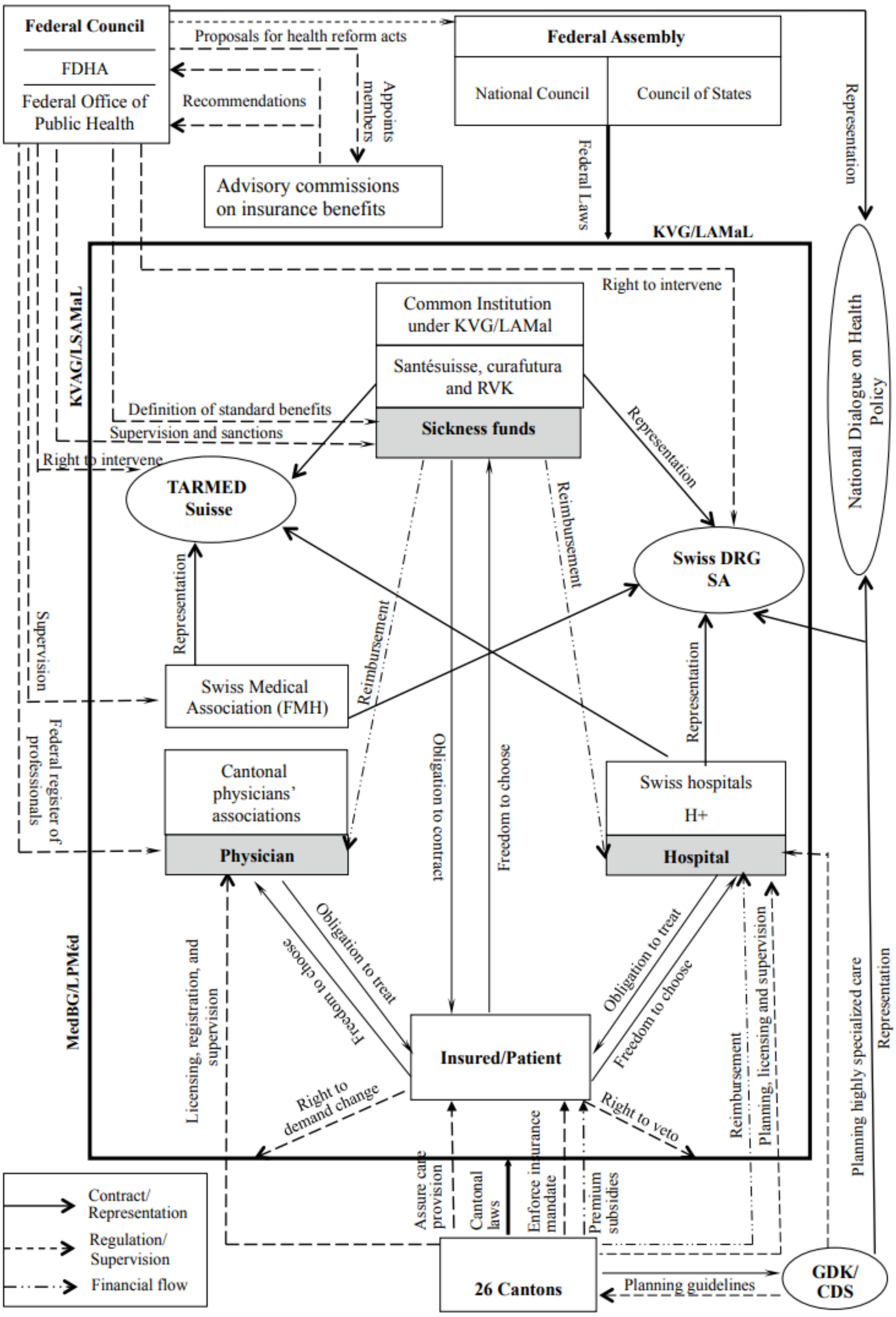

Figure 1: An overview of the health system organization in Switzerland (De Pietro et al., 2015, p. 20)

The Swiss healthcare system is among the most expensive in the world (Angerer & Liberatore, 2018, p. 13). In 2017, the cost of services provided by the healthcare system amounted to CHF 82.5 billion, equivalent to 12.3% of the GDP (BFS, 2019, p. 67). Healthcare costs have kept rising since 1995 at around 3.7% yearly (BFS, 2019, p. 67), especially in the support services area (e.g., public services, laboratory analysis) (Interpharma, 2020, p. 15). Among other causes, such as outpatient curative treatment, long-term care, inpatient curative treatment, and healthcare goods, which all account for over 80% of the total healthcare costs in Switzerland (BFS, 2019, p. 67), or multimorbidity in elderly people driving up the demand for health services (Angerer et al., 2017, p. 14), medical innovation is generally regarded as a reason for additional costs for the healthcare system, especially since many new technologies are used in the more expensive inpatient sector (Sorenson et al., 2013, p. 168). Growing wealth levels and the associated increased demands and expectations of the population for health services induce higher spending on health and, therefore, a corresponding overconsumption and increase in volume by service providers (Kocher, 2011, cit. in Angerer & Liberatore, 2018, p. 14). A system of regulated competition between nonprofit mandatory health insurers and service providers, such as the Swiss one, is believed to ensure cost containment while guaranteeing high-quality healthcare (Camenzind, 2016, p. 167). However, the high-density regulations with the intertwining of competencies between the different federal levels, alongside the private sector, complicate reforms, quality promotion, and effective control of cost growth (Angerer & Liberatore, 2018, p. 15).

2.2 Digitalization in the healthcare sector

Today, digitalization affects many sectors of the economy and society and can be described as the process of "transmission of the humans and their living and working worlds on a digital level" (Hamidian & Kraijo, 2013, cit. in: Meister et al., 2017, p. 188). In the healthcare sector, while digitalization plays a determinant role in providing medical innovations able to prevent, diagnose, and treat numerous diseases (Scheller-Kreinsen et al., 2011, p. 1166), it enhances communication between healthcare providers and patients by encouraging the latter to undertake prevention activities and entrusting them with direct responsibility for their own health (Lupton, 2013, p. 257). Reduction of healthcare expenditures is also among the positive outcomes believed to result from digital health (Tresp et al., 2016, p. 2180), although this argument remains debated: despite the important contributions of technological progress to improving health outcomes, innovations in healthcare are widely seen as the most important drivers of the increase in healthcare spending (Sorenson et al., 2013, p. 168; Rahimi, 2019, p. 108). Nonetheless, digitalization in the healthcare sector typically includes innovative software solutions and algorithms that might be significantly cheaper than devices or drugs. Moreover, digital technologies tend to focus on solutions for known inefficient delivery systems of healthcare rather than developing new treatments (Rahimi, 2019, p. 108). In this increasingly broad area of activities, terms such as "Health 2.0," "Medicine 4.0," "Connected Health," and the likes are interchangeably used; among these, however, "digital health" is the one that has developed and established itself over the years (Angerer et al., 2017, p. 7) and that has offered the broadest and most balanced spectrum of interpretation and an explicit conceptual link to the overarching trend of digitalization (Knöppler et al., 2016, pp. 24–25).

Under the umbrella term “digital health” fall any actions utilizing information and communication technologies (ICT) that are intended to benefit the quality of care and cost reduction to support management of chronic pathologies, home recovery, patient empowerment, and coordination among multiple actors (Serbanati et al., 2011, p. 621; Kostkova, 2015, p. 1). Knöppler et al. (2016, pp. 25–31) related three specific factors to this definition, which they identified as key drivers of digital health: technological innovation, a cultural change placing the patient at the center of their healthcare activities, and the health policy framework conditions. First, as the authors argued, cross-industry technological innovations account for the development of digital health; some of them have established themselves as specific manifestations of the healthcare market and therefore drive the impetus of digital health. Companies from various sectors are now investing considerably in the digital healthcare market (Angerer et al., 2017, p. 12). According to the market research firm statistics MRC, in 2017, the global digital health market was worth USD 183 billion, with an expected rise to USD 665 billion by 2026, which accounts for a compound annual growth rate of 15%. This massive increase can be partly reconducted to initiatives of leading healthcare companies, which are investing large sums in digital health (Angerer et al., 2019, p. 7). Second, digitalization improves how efficiently information is created, shared, and distributed; in the healthcare sector, effective and efficient sharing of information and knowledge with patients is crucial in generating value to the system (OECD, 2019, p. 97). With patients becoming more engaged, informed, and involved with their healthcare decisions, better, faster, and real-time access to care is therefore demanded; digital health thus plays an important role in meeting the patients’ needs, as it can bridge time and distance, educate and empower patients and to strengthen the caregiver–patient relationship (OECD, 2019, p. 97). However, the potentially infinite access to many sources of information has also made it increasingly difficult for many to distinguish what information and tools might be beneficial and useful to their own and others’ health; this is why many countries have begun to increase their efforts to provide patients and health systems’ users with information about their health (OECD, 2019, p. 97). This cultural change, where system users can directly access information about their own health—rather than to bear it in the hands of health professionals, who acted as arbiters of what to share—enables a behavioral change of citizens and patients for better health literacy and patient empowerment (Knöppler et al., 2016, p. 28; OECD, 2019, p. 97). The intention is therefore to support individuals in their own responsibility for maintaining health by allowing monitoring, management, and improvement of their health status (Meister et al., 2017, p. 190). Finally, the health policy framework also reflects on digital health, as it may act as a driving or inhibiting force, especially regarding licensing regulations for new medical devices and the financing of digital health applications (Knöppler et al., 2016, p. 29).

The extent to which digital health can benefit an existing (Swiss) healthcare system is determined by its inscription into the health value chain, positing that all players involved in the system must properly collaborate to create a high-added value for patients in the production of the product “health”(Angerer et al., 2019, p. 8). The literature identifies three dominant areas of change where digital health intervenes in the health value chain: information and prevention; contact points and patient flow; and diagnosis and therapy (Angerer et al., 2019, p. 13). Figure 2 overviews the three main areas of change in the health value chain through digital health:

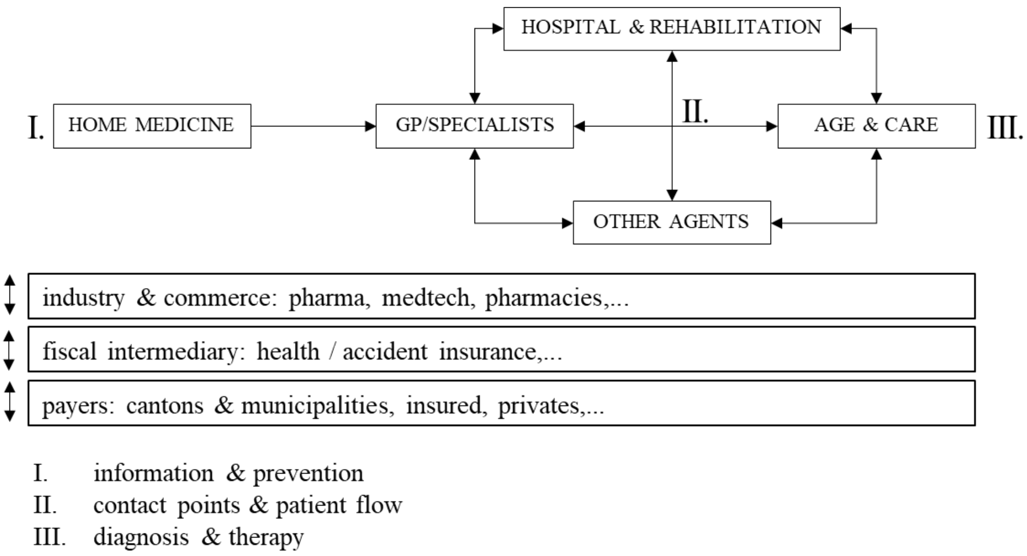

Figure 2: The three areas of change in the health value chain through digital health (Angerer et al., 2019, p. 13, own representation)

When facing a healthcare issue, patients initially seek to treat their condition at home (Angerer et al., 2019, p. 8). Here is where digital health can first be beneficial (Point I). As Angerer et al. (2019, p. 14) outlined, with the emergence of the informed patient, an increasing proportion of the population is concerned with their health and therefore requires engagement with their wellbeing and disease prevention. ICT utilization provided in digital health meets these patients’ needs. With increasingly more information available, the medical staff will also be challenged in providing quality advice, diagnosis, and treatment using their digital knowledge tools, expert systems, and new forms of interdisciplinary collaboration. Once the patients reach their limit in tackling their health issue, they enter a networked system of healthcare providers who attempt to diagnose and solve the medical problem together (Angerer et al., 2019, p. 8). Digital health here can coordinately transparently analyze and manage patient flow to avoid treatment at easily accessible but exorbitant players, such as the emergency room in hospitals or for professionals, to determine the right next point of care for the patient (Point II) (Angerer et al., 2019, pp. 14–15). Digital health helps healthcare professionals tackle different challenges they are confronted with when assessing a patient's health (Angerer et al., 2019, p. 15). Digital technologies' utilization can thus improve the current situation by providing virtual assistance systems to facilitate anamnesis or support analysis during diagnosis, improve diagnostic results by employing computer-aided analyses, and identify patterns and abnormalities in laboratory values using machine learning algorithms (Point III) (Angerer et al., 2019, p. 15). Nonetheless and in opposition to other economic sectors, where digitalization has been used to continuously improve services and products and create significant value on the supply and demand sides of the global economy (OECD, 2019, cit. in OECD, 2019, p. 17), the healthcare sector represents a stark contrast and is lagging behind in grasping digital momentum (OECD, 2019, p. 17). As the literature reveals, the lack of digital progress in healthcare is mainly traceable to structural, organizational, and institutional barriers that are hardened and firmly embedded in healthcare systems, thus resulting in fragmentation and silo thinking. Overcoming these barriers thus requires overhauling existing institutional and policy frameworks that control health systems behavior (OECD, 2019, p. 32).

2.2.1 eHealth and telemedicine in Switzerland during the COVID-19 pandemic

With the advent of the Internet in the 1990s, new communication channels for medical information systems were paved, which induced less importance of physical proximity to the benefit of information and communication technologies (Angerer et al., 2017, p. 7). This evolution induced the notion of "eHealth." In Switzerland, the concept of eHealth, electronic health services, was outlined in the first "eHealth Strategy Switzerland" by the Swiss Federal Council in 2007, referred to as "the integrated use of ICT to design, support, and network all processes and participants in the healthcare system" (BAG, 2007, p. 13). Hence, eHealth encompasses various services or systems for positioning ICT in healthcare, not by underlying what is technically feasible (Eysenbach, 2001, p. 1) but rather by linking and simplifying the existing processes to establishing new and better ones (BAG, 2007, p. 13). While Showell and Nøhr (2012, p. 883–884) illustrated that consensus regarding eHealth's definition seems absent, they also specified that the salient components of common and agreed eHealth actions can still be strategized, although a single consensus definition is not achievable. Therefore, it is commonly agreed that eHealth specifically focuses on synergizing electronic communication and medical information technology (Hoseini & Zare, 2020, p. 66). Electronic prescriptions, electronic health records (EHR), mHealth (mobile health), and telemedicine fall under eHealth initiatives (Hoseini & Zare, 2020, p. 66).

Telemedicine is the digital health topic with probably the longest history; discussions and solutions on the remote interaction between patient and doctor have been conducted since the 1980s (Angerer et al., 2017, p. 54). Telemedicine encompasses the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or pictures, to the actual treatment, health education, and transfer of medical data (Stowe & Harding, 2010, p.196; Angerer et al., 2017, p. 11). Other than diagnosis, telemedicine also benefits disease prevention and surveillance, treatment and adherence, alongside lifestyle and patient engagement (Golinelli et al., 2020, p.2). While easier access to medical services (especially in rural areas) and expected cost savings are considered the main reasons for telemedicine's introduction (Committee on Evaluating Clinical Applications of Telemedicine, 1996, p. 18), telemedicine can realize pooling effects (i.e., the creation of a collective pool of qualified resources, here being medical professionals) through healthcare providers' centralization (Angerer et al., 2019, p. 14). Using collective pools, fluctuations in overload or underload derived from decentralized units are ideally discarded, allowing costs to be optimized and patients to benefit from both a higher availability and a better level of knowledge of the medical staff (Angerer et al., 2019, pp. 14–15). In sum, the benefits from telemedicine encompass the protection of health professionals and patients, the possibility of enabling remote work for healthcare providers, better access to healthcare, saving on supplies and hospital beds, and support for specialty care (Clipper, 2020, p. 501). In Switzerland, telemedicine applications began in the 2000s in a rapidly, mostly uncoordinated manner and were launched on an institutional or individual initiative base (Eckhardt et al., 2004, p. 14). Telemedicine in Switzerland initially spread within specialties involving the transmission of high-quality imaging data, such as (tele-) pathology, (tele-) radiology, or (tele-) dermatology. Following the rising healthcare costs and resulting scarcity of resources, it eventually moved to a more encompassing understanding of "telehealth," thus emphasizing its public health character for integrating telecommunications into basic care to favor health promotion (Denz, 2003, p. 2). Today, different companies partner with Swiss health insurance companies in offering telemedicine, with Medgate being the largest. Founded in 1999, Medgate is active in the market for electronically supported healthcare services, bringing telemedicine services (interaction between doctor and patient) and IT services for telemedicine under one roof (Osl et al., 2009, n.p.). Moreover, special insurance models have been set up to offer insured persons the option to first contact their insurance partner's telemedicine center for all medical concerns, where they receive medical advice and have their treatment coordinated (Von Gossler & Klauser, 2017, p. 335). Nevertheless, the annual Swiss eHealth barometer reveals that telemedicine utilization among Swiss healthcare actors is still stagnant despite offering a relatively mature telemedical ecosystem (Nittas & Von Wyl, 2020, p. 1). While telemedicine utilization in Switzerland has hardly changed in percentage since 2014, telemedicine, in relative terms, is most widespread among hospitals and general practitioners (around 10% each), and employing these digital options constantly tends to zero among the remaining healthcare professionals (gfs. Bern, 2020, p. 27). With the COVID-19 pandemic, a reverse trend has been observed: with the physical proximity being replaced by distancing and limited access to certain types of care (Nittas & Von Wyl, 2020, p. 1), telemedicine has been widely utilized to care for patients at home with mild COVID-19 or COVID-19 symptoms and to medically manage non-COVID-19-related issues (Tsikala Vafea et al., 2020, p. 254). A recent study conducted among Swiss healthcare providers both before and after the COVID-19 pandemic outburst shows that, with the pandemic, the Swiss healthcare system experienced a striking digitalization push (KPMG, 2020, p. 16): high investment sums were immediately approved, medical processes underwent a digitalization boost, patients demanded more and more digital solutions, and a culture change among employees was induced (KPMG, 2020, p. 19) More importantly though, all respondents indicated that telemedicine had significantly gained in meaning and is currently considered the industry standard (KPMG, 2020, p. 16).

3. THEORETICAL BACKGROUND AND LITERATURE REVIEW

3.1 Organizational technology adoption

The term *technology adoption* refers to an organization's decision to acquire a technology and offer it to its members to support or ameliorate their task performance (E. M. Rogers, 1995, cit. in P. J.-H. Hu et al., 2002, p. 199). Adoption theories investigate individuals and their choices to accept or reject an innovation; in some models, adoption also encompasses the extent to which the innovation is integrated into the context (Straub, 2009, p. 626). Within the framework of *organizational* technology adoption, technology utilization, its service level, and organizational competitiveness are analyzed (P. J.-H. Hu et al., 2002, p. 198). Although a unique model outlining the process that an individual undergoes before adopting an innovation is lacking, historically, adoption is considered regarding some behavioral changes (Straub, 2009, p. 626). The contribution of a new technology within an organization can only be realized when and if the technology is widely diffused among the members of the organization (Hall & Khan, 2003, p. 1). Although the final decision whether to adopt a technology entails a dichotomous answer (yes/no), the process leading to it may involve a series of specific phases that determine how technological changes occur; understanding the determinants of the diffusion process is therefore essential to understand adoption (Hall & Khan, 2003, p. 1; P. J.-H. Hu et al., 2002, p. 199). While *diffusion* refers to "the process by which an innovation is communicated through certain channels over time among the members of a social system," *innovation* refers to "an idea, practice, or object perceived as new by an individual or other unit of adoption" (E. M. Rogers et al., 2009, p. 418). Innovation does not necessarily have to be objectively new, as it possesses the perception of being new, nor does it need to be better or more beneficial to an individual (Straub, 2009, p. 626). Diffusion theories examine how an innovation spreads through a population across time; sometimes, they examine elements such as time and social pressures to clarify how a population adopts, adapts to, or rejects this innovation (Straub, 2009, p. 626). In sum, whereas adoption describes an individual's decision whether to integrate an innovation into their life, diffusion concentrates on the collective adoption process over time (Straub, 2009, p. 629). The challenge of understanding, predicting, and explaining the factors relevant to technology adoption has concerned many researchers over the past three decades, resulting in numerous technology acceptance theories and models exploring the determinants of users' adoption decisions (Tarhini et al., 2015, pp. 58–59).

Among these, E. M. Rogers' diffusion of innovation theory (DOI) is one of the most prominent approaches for analyzing technology adoption (P. J.-H. Hu et al., 2002, p. 200) and is considered a fundament in formalizing technology adoption, serving as a reference base for other technology acceptance models (Tarhini et al., 2015, p. 60). DOI posits that innovation characteristics operating at both the individual and the organizational level are drivers to adoption, and these characteristics include the relative advantage the innovation carries with it compared to its precursor, its compatibility with the different adopters' group's beliefs and backgrounds, and its complexity (ease of use), trialability (practical ease of use), and observability (ease of understanding within an organization) (Tarhini et al., 2015, p. 60; Molinillo & Japutra, 2017, p. 35). Following five stages, from the knowledge about the innovation to the decision to adopt or reject it (Tarhini et al., 2015, p. 60), specific categories of individuals involved in the decision process follow a path of adoption that can be modeled as an S-shaped curve: starting with a first group of innovators acting as system gatekeepers who understand and handle the large amount of information and uncertainty on the innovation, early adopters take over and shape the role of adoption, followed by the early and late majority, up to laggards, which are the last group of adopters in the adoption process (Tarhini et al., 2015, p. 61). According to this time path of usage, diffusion rates slowly rise at first when there are few adopters, then accelerate to a maximum, and finally increase at a slower rate again when approaching to satiation (E. M. Rogers, 2010, p. 257), creating the so-called S-curve of diffusion (E. M. Rogers et al., 2009, p. 427). Along with DOI, the technology acceptance model (TAM) by Davis (1989) represents a central theory in technology adoption research (Plewa et al., 2012, p. 750) and was specifically developed for explaining and predicting user acceptance of computer technology (P. J.-H. Hu et al., 1999, p. 93). TAM is grounded in Fishbein and Ajzen's (1975) theory of reasoned action (TRA), which relies on the hypothesis that individuals typically think about their action implications before making any decision or undertaking any behavior (Ajzen & Fishbein, 1980, cit. in Tarhini et al., 2015, p. 63). TAM adjusts this relationship to an IT-user acceptance model (P. J.-H. Hu et al., 1999, p. 94), positing that perceived usefulness and perceived ease of use are crucial elements in predicting an individual's attitude and intention to use a new technology (Bradley, 2012, p. 21; Plewa et al., 2012, p. 750). Perceived usefulness is determined from the prospective user's viewpoint, investigating whether applying the new technology will improve job performance within the organization, whereas perceived ease of use describes the user's perception that the system will be easy to use, which in turn influences the user's perceived usefulness (Bradley, 2012, p. 23). DOI and TAM share some similarities in that both theories identify the perceived attributes of an innovation as key factors predicting adoption, consider users' intentions to adopt a technology as their dependent variable, and are applied more easily to situations where individuals can freely choose whether to adopt the innovation (Gallivan, 2001, p. 54). Nonetheless, these traditional frameworks are considered reductive since they fail to recognize the realities of implementing technology innovations within organizations, in particular when adoption decisions are made at the organizational level instead of the individual level (Gallivan, 2001, p. 51). Moreover, they ignore that innovation attributes can be perceived differently depending on the organization's different contexts involved (P. J.-H. Hu et al., 2002, p. 200). Some studies have argued that in applying traditional frameworks such as DOI and TAM, the outcomes of adoption are sensitive to the fit between the assumptions underlying these models and the specific characteristics of the adoption context and the technology under observation (Gallivan, 2001, p. 55; P. J.-H. Hu et al., 2002, p. 200). As the literature specifies, although the fallouts of adoption are typically measured regarding behavioral change (Straub, 2009, p. 627), relevant contexts must be considered to properly address important issues in probable technology adoption (P. J.-H. Hu et al., 2002, p. 198).

Among the different frameworks developed to address this issue, the technology-organization-environment framework (TOE), elaborated by Tornatzky and Fleischer (1990), accounts as a comprehensive outline for analyzing technology adoption at the organizational level (P. J.-H. Hu et al., 2002, p. 200; Molinillo & Japutra, 2017, p. 35). TOE suggests that technology adoption decisions are jointly influenced by three specific elements: technological, organizational, and environmental contexts (Molinillo & Japutra, 2017, p. 37). The *technological context* encompasses all the technologies relevant to the organization, both those already in use and those existing outside the organization but not yet employed (Baker, 2012, p. 232). Considering the technological context when introducing innovations is crucial to organizations, as they are required to ponder the organizational changes that will result from the adoption. Some innovations might dramatically impact the organization, requiring it to make quick and significant adoption decisions to maintain its competitive standing (Baker, 2012, p. 233). The *organizational context* relates to the organization's characteristics and resources, linking structures between employees, communication processes within the organization, its size, and the amount of slack resources (Baker, 2012, p. 233). Finally, the *environmental context* refers to the macro-environment in which the organization makes acceptance decisions (Jia et al., 2019, p. 4) or, alternatively, to the structure of the organization, the presence or absence of technology service providers, and the regulatory environment (Baker, 2012, p. 234). TOE has received widespread validation in explaining technology adoption in organizations across different economic sectors and cultural contexts, where the three elements of technology, organization, and environment have been confirmed to influence the way an organization recognizes the need for pursuits and adopts a new technology. (Baker, 2012, pp. 235–236; Molinillo & Japutra, 2017, p. 36). With TOE, technology adoption at the organizational level is conceptually depicted by establishing a framework in which specific factors can be identified within the respective contexts (P. J.-H. Hu et al., 2002, p. 199). Although, as argued by Baker (2012, p. 237), most of the theoretical developments around TOE have been limited in listing the different factors relevant to the various adoption contexts and, therefore, no new constructs have been added to the framework, the flexibility to vary factors or measures for each new research context allows the TOE framework to be highly adaptable, with little need for adjustment or refinement of the theory itself (Straub, 2009, p. 237). It is then safe to say that, provided that new technologies are developed, the need to understand their adoption within organizations makes the TOE framework capable of providing insights for scholars and professionals (Baker, 2012, p. 241).

As opposed to extensive research on technology adoption focusing on the individual level, individuals' resistance to technologies has been limitedly studied (Laumer & Eckhardt, 2012, p. 63). Resistance results as a natural response from the recipients of change within an organization to a perceived threat or an alteration of the status quo, to their own personal security, to the ability to perform, or even because of resentment or distrust feelings toward the agents (Ford et al., 2002, p. 105). When confronted with a new technology, users may react in different ways other than fully adopt it: they might reject it completely, partially use its functions, actively resist it, or unwillingly accept it (Laumer & Eckhardt, 2012, p. 65). At the organizational level, this translates into Lewin's (1947) conceptualization of change, according to which change occurs as the unfreezing of a status quo caused by altering some forces maintaining the initial equilibrium—either a weakening of the barriers preserving the initial situation or the strengthening of the driving forces (Dent & Goldberg, 1999, p. 30). In holding this view, Lewin maintained that since change occurs within a complex system of different roles, attitudes, behaviors, norms, and similar, they all want to preserve the equilibrium and thus result in resistance (Dent & Goldberg, 1999, p. 30; Elrod & Tippett, 2002, p. 274). Lewin argued that the success of change depends on the organization's ability to "unfreeze" the equilibrium by altering the dynamics of the forces before successfully implementing change (Bhattacherjee & Hikmet, 2007, p. 727). Resistance is hence focused on the drift from the status quo caused by new technology utilization, acting as a cognitive force possibly precluding a behavioral change (Lewin, 1947, cit. in Bhattacherjee & Hikmet, 2007, p. 728). Resistance therefore represents a possible antecedent to acceptance that must be overcome to enhance successful adoption of the innovation by the organization (Bhattacherjee & Hikmet, 2007, p.

728). Hence, resistance is not a direct object of this investigation, which assumes an ongoing adoption process.

3.2 Organizational adoption of telemedicine

Researchers agree with Tornatzky and Fleischer’s (1990) original approach that the three TOE contexts influence adoption and assume that for each specific technology or context being studied, there is a unique set of factors or measures (Baker, 2012, p. 236). TOE has been tested in various organizational settings, including healthcare, generating significant conclusions or results regarding technology adoption in the healthcare field (Chowdhury et al., 2019, p. 5). Regarding telemedicine, the TOE framework provides in this sense an adequate approach, as it accounts for most of the important technology adoption factors identified in previous case studies on telemedicine technology adoption by healthcare organizations (P. J.-H. Hu et al., 2002, p. 201). For a long time, research on telemedicine has focused on technological developments or clinical applications, failing to analyze technology management from a decision-making perspective (Sheng et al., 1999, pp. 265–266). With the surge of telemedicine as an IT-based innovation that can support and improve both patient’s care and organizational competitiveness, the need to thoroughly consider various technological, social, cultural, and organizational dimensions accompanying telemedicine introduction was made clear (P. J.-H. Hu et al., 1999, p. 95). Findings on organizational technology adoption of telemedicine are therefore abundant and identify healthcare providers as the most important initial gatekeepers for deploying telemedicine (Whitten & Mackert, 2005, p. 520). Physicians in particular are found to positively impact the successful adoption of technology in healthcare organizations (Ingebrigtsen et al., 2014, p. 402). In this light, several studies have identified providers’ perceived usefulness of telemedicine as the key factor for its adoption (i.a., Sheng et al., 1999, p. 269; Croteau & Vieru, 2002, n.p.; P. J.-H. Hu et al., 2002, p. 213). Alternatively, physicians tend to concentrate on the usefulness of telemedicine in their daily activities, requiring telemedicine to prove itself to serve the needs of modern healthcare, which underscores the need for decision-makers to prove the utility of the innovation (Croteau & Vieru, 2002, n.p.). Physicians are less likely to use telemedicine unless its technical feasibility is corroborated by medical or service validity (Tanriverdi & Iacono, 1998, cit. in P. J.-H. Hu et al., 2002, p. 203). In their study on telehospice and telepsychiatry projects in Michigan, Whitten and Mackert (2005, pp. 519–520) found the perceived ease of use of the technology for healthcare providers (such as postulated by the TAM framework), alongside the incentives to promote provider acceptance, to be enablers of telemedicine adoption. Ease of use itself of telemedicine is also crucial to adoption: end users are likelier to adopt the technology when the innovation is designed with intuitive interfaces (Menachemi et al., 2004, p. 630). As Croteau and Vieru (2002, n.p.) indicated, the reactions of potential adopters of telemedicine are also conditioned by the different backgrounds and environment they live in. To Swiss physicians in particular, expectations of the workload and interoperability with the current systems, security, and liability are the main factors influencing telemedicine adoption (Nittas & Von Wyl, 2020, p. 2). The demographics of Swiss doctors also play a significant role since some might lack the necessary digital affinity to adopt telehealth and hence present digital literacy gaps (Nittas & Von Wyl, 2020, p. 2). Ranganathan et al. (2020, p. 220) analyzed organizational factors capturing possible barriers to telemedicine adoption, such as high costs of equipment, hosting, and staff; lack of staff expertise and training; lack of staff support; redesign of workflows; lack of demand for telemedicine; non-availability of physicians and clinicians; and lack of adequate coverage or reimbursement from payers. Lack of staff expertise and training, lack of staff support, and non-availability of physicians and clinicians were non-significant, whereas high costs of equipment and lack of demand for the service were found to be negatively associated with telemedicine adoption, hence acting as adoption inhibitors (Ranganathan et al., 2020, pp. 222–223). Finally, reimbursement tariffs for digital services and regulation of data protection and privacy are also expected to influence technology adoption (Nittas & Von Wyl, 2020, p. 2). Hospital characteristics are likewise proven to be influential for telemedicine adoption: Gagnon et al. (2005) found structural features such as functional differentiation (i.e., the total number of work subunits in the hospital), the size and localization of the hospital, or the decision to upgrade or remove telehealth equipment to be significantly associated with telemedicine adoption. More recent studies examining the adoption of telemedicine by ambulatory clinics in Minnesota (US) found clinic characteristics such as ownership (physician-owned practice or health system owned), location (urban or rural) type of clinic (primary or specialty), or if the clinic handled behavioral/mental health issues to be statistically significant predictors for telemedicine adoption, where clinics owned by a health system had 165% higher odds of telemedicine adoption compared to physician-owned independent ones (Ranganathan et al., 2020, p. 221). Economic issues related to cost savings are also viewed as drivers of adoption: especially to hospital administrators, returns on investment demonstrating the economic benefits of telemedicine facilitate its adoption (Menachemi et al., 2004, p. 627). Finally, the influence of technology-related factors on telemedicine adoption, meaning that the organization is already familiar to some extent with technology-related instruments, has proven to be a significant predictor for telemedicine adoption: organizations that have little experience with digital-based solutions and lack health information exchange capabilities lag behind in telemedicine adoption (Ranganathan et al., 2020, p. 222). P. J.-H. Hu et al. (2002), for their part, proposed a revised TOE framework for targeted technology adoption involving most of the public healthcare organizations in Hong Kong and then proceeded to identify important factors responsible for the technology adoption of telemedicine: PEOU, PTS, PSB, PSR, CAM, and PSN. These factors are the focus of the following analysis.

4. RATIONALE BEHIND MODEL ESTIMATION

To determine variables that cannot be directly measured, as in the factors identified by P. J.-H. Hu et al. (2002), a so-called *factor analysis* must be performed (Hoyle, 2000, p. 465). The basic assumption of factor analysis is to investigate the relationships and patterns among a collection of *observed variables* by regrouping them into a limited set of clusters based on shared variance to isolate constructs and concepts—so-called "factors" or "latent variables" (Yong & Pearce, 2013, pp. 79–80). *Latent variables* are complex social or psychological phenomena that are best measured with multiple observed items, i.e., the variables that constitute a database (Bowen & Guo, 2011, p. 17). Factor analysis thus serves to determine the amount of latent variables that can be assessed by a set of observed variables (Fabrigar & Duane, 2012, p. 3) by seeking the simplest method of interpreting the observed data (parsimony) (Yong & Pearce, 2013, p. 79). There are two types of factor analysis techniques: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Orçan, 2018, p. 414). EFA is performed to determine underlying factors among the observed variables, that is, when there is no knowledge about which items determine which factors (Orçan, 2018, p. 415). EFA assumes common latent factors in the dataset influencing the variables and seeks to find the smallest number of common factors that will account for the correlations (Fabrigar & Duane, 2012, p. 6; Yong & Pearce, 2013, p. 80). While EFA is a technique aimed at *exploring* an existing structure and is commonly used in scale development (Orçan, 2018, p. 415), CFA is used to *confirm* the factorial validity of models resulting from EFA (Yong & Pearce, 2013, p. 91). In other words, in EFA, data is explored and yields information on the number of factors needed to represent the data; with CFA, the number of factors is predetermined by theory or past research, and so is the relationship between the measured variables and the respective latent variables; how well the observed variables represent the number of constructs is the specific focus of CFA (Bowen & Guo, 2011, pp. 9–10). Figure 3 illustrates the rationale behind these models.

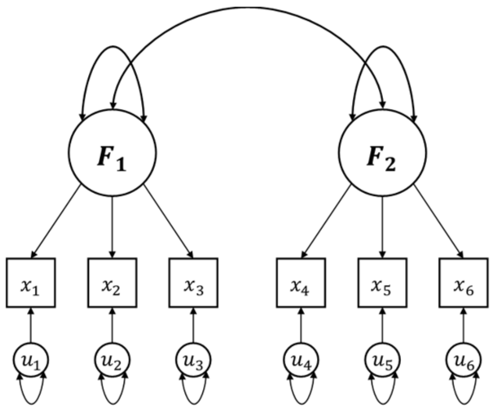

Figure 3: Path diagram of two correlated factors, modeled using CFA (Hoyle, 2000, p. 467, own representation)

F_1 and F_2 represent two latent variables or factors; x_1 through x_6 stand for the observed variables that, respectively, measure each factor; u_1 through u_6 represent the measurement errors in each item. One-way arrows represent paths, essentially, the causing effect of a factor on an item, while two-way arrows represent either variance or covariance. When estimating such models, only paths and variance/covariance are estimated (Acito et al., 1980, p. 143). Alternatively, this statistical approach isolates the component truly accounting for the measurement of the latent variable (x_1 through x_6) and remove the error. Since it is impossible to identify the value of the observed variable when having two unknown parameters like true score and error, it is necessary to include multiple indicators of the latent variable (Thakkar, 2020, p. 3). CFA was therefore used in this study to answer the first research question of whether the hypothesized six-factor structures by P. J.-H. Hu et al. (2002) adequately fit with the sample data. Although CFA is often used as a single statistical strategy to test hypotheses about the relations among a set of variables (Hoyle, 2000, p. 465), structural equation modeling (SEM) is usually preferred, as it acts as a general model combining both factor and multivariate statistical analysis (Bowen & Guo, 2011, p. 5). The rationale behind SEM is that it allows estimation in a single analysis model containing predicted and predictor variables simultaneously (Bowen & Guo, 2011, p. 6). Alternatively, it allows the investigation of both the constructs emerging out of sets of observed variables and the relationships among those constructs (Thakkar, 2020, p. 1). Similar to traditional "regressions," SEM acts as an umbrella for numerous statistical methods—CFA, among others (Brown, 2006; MacCallum & Austin, 2000, cit. in Jackson et al., 2009, p. 6). CFA therefore represents a specific component of a *general structural equation model*, namely the so-called *measurement model*, as it accounts for how the latent variables are *measured* (Hoyle, 2000, p. 465; Bowen & Guo, 2011, p. 6). When estimating the measurement model, latent variables with adequate statistical properties can be identified and hence used for cross-sectional and longitudinal regression analyses; consequently, the strength and direction of relations between the constructs are tested and then held in a *structural model* (Bowen & Guo, 2011, p. 6; Hoyle, 2000, p. 466). The structural model, therefore, involves investigating the relationships between constructs similar to a regression. However, since this study intends to secondarily examine the effect of the six identified factors on an observed—rather than latent—dependent variable "adoption," the second step of the analysis included the application of a different type of SEM, namely *path analysis*. Similar to CFA, path analytic models are a subset of SEM testing the structural hypotheses of both direct and indirect causal relationships between observed variables (Thakkar, 2020, p. 17) rather than latent variables. Path analysis allows for performing multivariate analysis to estimate structurally interpretable terms—the direct, indirect, and total effects among a set of variables—assuming an a priori theory-derived structure of the involved variables (Mueller, 1996, p. 22). Path analysis was therefore used to answer the second research question of how the six hypothesized factors by P. J.-H. Hu et al. (2002) predict telemedicine technology adoption in Swiss healthcare organizations.

5. CONFIRMATORY FACTOR ANALYSIS

5.1 Measurement hypotheses

Since the measurement model applies to the relations between latent and observed variables, measurement hypotheses were first tested (Sarmento & Costa, 2019, n.p.). Measurement hypotheses define a priori which observed variables and factors should be included in the model, alongside how these variables relate to one another (Lewis, 2017, p. 240). This requires a substantive review of relevant theory and prior research to justify the posited relationships within the model (Suhr, 2006, p. 1). The six constructs identified by P. J.-H. Hu et al. (2002) are described by 18 observed variables; Table 1 overviews the identified factors and their associated items, as proposed by the authors. In the first step, based on the empirical grounds of P. J.-H. Hu et al. (2002), the relationship between constructs and observed variables was therefore tested against the hypotheses that follow.

<u>Technological context</u>

(1) PEOU

Ease in becoming skillful and flexible interaction

Studies on PEOU measurability resort to its intrinsic aspects, that is, the tasks in which the technology itself delivers the product or service for which the technology is ultimately being used (Gefen & Straub, 2000, p. 4). When measuring PEOU, one also measures users' assessments of ease of use and ease of learning or, alternatively, whether the intrinsic characteristics of the technology help to perform a job better (Lin, 2013, p. 245). Learnability is in this sense a key attribute of ease of use: remembering how to perform tasks is a phenomenon found to be deeply associated with the learning process to use a new system (Davis, 1989, p. 325). To become a skillful user, the procedure for using a specific technology should be easy to memorize (Nielsen, 1993, cit. in Lin, 2013, p. 245). Flexibility, on the other hand, is found to be associated with functionality; hence, the ability of a system to provide the functions that users need to perform their tasks (Goodwin, 1987, p. 229) was found to be especially effective on the ease of use of expert users (Goodwin, 1987, p. 231). Ease in becoming skillful and flexible interaction account for the two items contained in the ease-of-use scale developed by Davis (1989), which are hypothesized to be fundamental determinants of user acceptance of information technology (Adams et al., 1992, p. 227), as addressed in his technology acceptance model (TAM) (Plewa et al., 2012, p. 750) and are therefore solidly grounded.

Hypothesis 1 (H1): The relationship between item ease in becoming skillful and the latent construct PEOU is strongly positive and statistically significant.

Hypothesis 2 (H2): The relationship between the item flexible interaction of telemedicine and the latent construct PEOU is strongly positive and statistically significant.

(2) PTS

Technology certification by government authority

Debates on the legal and ethical implications of telemedicine originated even before specifically designed devices were developed; with the rapid expansion of remote-driven systems, discussions around legal implications and security requirements have risen, stressing the low level of maturity in this area (Parimbelli et al., 2018, p. 91). Legislation and policy therefore account for some of the main determinants for successful telemedicine adoption: systems that conform to a certain standard are likelier to be accepted by telemedicine users (Broens et al., 2007, p. 307). The regulatory framework plays a decisive role in defining the security terms of the technology (Parimbelli et al., 2018, p. 96).

Hypothesis 3 (H3): The relationship between the item certification by government authority and the latent construct PTS is strongly positive and statistically significant.

Technology endorsement by medical professional societies

In aspiring to provide an educational experience for their members, professional medical societies shape clinical practice and influence patient care directly (Dalsing, 2011, p. 41). Professional societies supervise new technologies' utilization under their realm of application and often deliver checks and balances on other decision-making organizations (Feldman et al., 2007, p. 61). The authors argue that technology assessments by independent organizations, such as medical societies following government approval, can help identify truly beneficial and safe medical technologies, motivate research to answer lasting questions, and educate public and health professionals about the potential benefits and pitfalls of the new technology (Feldman et al., 2007, p. 62).

Hypothesis 4 (H4): The relationship between the item endorsement by medical professional societies and the latent construct PTS is strongly positive and statistically significant.

(3) PSB

Improving the timeliness of patient care

Assessment of service benefits requires multiple criteria; among these and in the realm of telemedicine applications, the literature offers a systematization into three benefit-related criteria: clinical outcomes, cost containment, and access to the technology (Zanaboni & Lettieri, 2011, n.p.). Clinical outcomes refer to a wide set of measures defining the effects of the implementation of telemedicine applications on patients' health status (Hailey et al., 1999, cit. in Zanaboni & Lettieri. 2011, n.p.). Measures of clinical outcomes include, among others, timeliness of patient care, therapeutic effectiveness of patient care, and indicators of transfer or admissions of patients (Zanaboni & Lettieri, 2011, n.p.). Timeliness of patient care is particularly imperative when intervening in rural or remote areas; in this sense, the benefits of telemedicine become apparent for providing prompt and quality emergency care (Mohr et al., 2018, p. 590). Also, telemedicine may provide surge capacity in busy rural emergency departments for local events that may quickly overwhelm available resources (Mohr et al., 2018, p. 590). Finally, telemedicine providers can probably conduct triage alongside local emergency providers to assist in allocating limited resources to organize the care team and the equipment to enhance a timely response on patient arrival (Mohr et al., 2018, p. 590). Studies have found telemedicine utilization to be positively associated with significant improvements in timeliness of healthcare compared to usual care (i.a. Whited et al., 2004; Fox et al., 2007; Anderson et al., 2017; Mohr et al., 2018), thereby accounting for the rationale of benefits that telemedicine provides.

Hypothesis 5 (H5): The relationship between the item timeliness of patient care and the latent construct PSB is strongly positive and statistically significant.

Improving the overall effectiveness of patient care

In a more managerial sense, effectiveness refers to the extent to which "planned outcomes, goals, or objectives are achieved due to an activity, intervention, or initiative intended to achieve the desired effect under ordinary circumstances (not controlled circumstances such as in a laboratory)" (Burches & Burches, 2020, p. 2). When applied to the healthcare sector, the understanding of effectiveness relates to the effect of medical intervention in changing the natural history of a particular disease for the better (Cochrane, 1972, cit. in Burches & Burches, 2020, p. 2). To be considered effective, telemedicine must therefore prove to enhance healthcare outcomes through its services (Zhai et al., 2014, p. 1). Regarding the dramatic advances in the information and communication sector, numerous studies have investigated the positive impact of telemedicine on clinical outcomes. However, despite the claimed high potential for developing clinically impactful healthcare through telemedicine, irrefutable evidence regarding the positive impact of telemedicine on clinical outcomes is still lacking (Ekeland et al., 2010, p. 737). Several reviews on the clinical effectiveness of telemedicine conclude that the evidence is still limited and inconsistent (i.a., Currell et al., 2000; Ekeland et al., 2010; Tsou et al., 2020; Zhai et al., 2014). This results indicate that the focus on service benefits needs therefore to explore new questions surpassing those of clinical effectiveness (Ekeland et al., 2010, p. 741).

Hypothesis 6 (H6): The relationship between the item effectiveness of patient care and the latent construct PSB is moderately positive and statistically significant.

Reducing unnecessary transfers or admissions

Especially in emergencies, the need to provide rapid and high-quality care to patients with time-sensitive conditions has been proven to be contingent on rapid diagnostics and treatment interventions (Mohr et al., 2018, p. 582). Also, patients discharged from the hospital after an acute event often require specialized follow-up by a personnel-and cost-intensive multidisciplinary team requiring on-site primary management (Goldberg et al., 2003, p. 706), or their transportation is either difficult, time consuming, and expensive (Rees & Bashshur, 2007, p. 672). Telemedicine delivers in this sense a possible solution in healthcare delivery and provides early diagnosis and tailored therapeutic intervention, coupled with enhanced appropriateness of hospital admissions and referrals to the emergency departments (Scalvini et al., 2000, and Scalvini et al., 2005, cit. in Giordano et al., 2009, p. 193). Telemedicine increases the information available to the medical coordinator at the time of referral, which benefits the appropriate transfer to the most appropriate care destination alongside care during transport (Kyle et al., 2012, pp. 149–150). Some studies conclude that telemedicine programs decrease the number of unnecessary transfers and over-triage, allow the patient to be treated locally, benefit them by changing the decisions of medical coordinators for the better, or confirm decisions already made (Kyle et al., 2012, p. 150; Langabeer et al., 2016, p. 718; Rees & Bashshur, 2007, p. 672). However, the literature reveals that this can also translate into higher local hospital admissions and reduced discharges after teleconsultation, probably inducing an additional burden on small rural hospitals (du Toit et al., 2019, p. 14).

Hypothesis 7 (H7): The relationship between the item reduced unnecessary transfers or admissions and the latent construct PSB is moderately positive and statistically significant.

Reducing patient care and service costs

Cost containment describes the value of resource use related to an intervention (Field, 1996, cit. in Zanaboni & Lettieri. 2011, n.p.), providing insight into whether telemedicine application is cost saving or cost effective (Zanaboni & Lettieri, 2011, n.p.). To be perceived as beneficial to adopters, telemedicine must prove to be cost effective compared to usual care; however, the possible benefits of telemedicine regarding cost effectiveness are yet unclear: even if the same health outcome can be realized through telemedicine the way they are with conventional care, differences in costs to patients, services, acceptability, or issues of equality may arise, bearing new types of cost implications (Currell et al., 2000, p. 3). Several studies therefore report inconclusive findings regarding the cost effects on the benefits of telemedicine (Ekeland et al., 2010; Tsou et al., 2020), alongside the impact that telemedicine programs have on health outcomes over conventional care (Zhai et al., 2014, p. 8). Evidence for the clear cost effectiveness of telemedicine seems to depend on the specific disease, the geographic area, or the type of service offered (Ekeland et al., 2010, p. 741).

Hypothesis 8 (H8): The relationship between the item reduced patient care and service costs and the latent construct PSB is positive and statistically significant, while the magnitude of the association is expected to be low.

Improving the service productivity of medical staff

Concerns over the growing costs of healthcare have put the performance of healthcare systems under increasing scrutiny (Moffatt et al., 2014, p. 686). On a general level, productivity refers to a productive organization attribute or a production function characteristic, indicating how efficiently inputs are transformed into outputs (Kämäräinen et al., 2016, p. 290). From a technological viewpoint, the effective use of IT systems can increase productivity by offering rapid access to resources and information (Ennis-Cole et al., 2018, p. 243). In this light, telemedicine is proven to enhance productivity regarding reduction of travel time or home visits for the medical staff (Dávalos et al., 2009, p. 940), enabling rapid re-deployment of staff after an emergency (Langabeer et al., 2016, p. 716) or, more generally, the reduction of service costs (Bashshur et al., 2016, p. 367). However, as health services are provided in different production modes, several factors make measuring healthcare productivity challenging (e.g., emergency departments vs. continuous patient care), which makes the connection between service production and benefit unclear (Kämäräinen et al., 2016, p. 289).

Hypothesis 9 (H9): The relationship between the item improved productivity of medical staff and the latent construct PSB is moderately positive and statistically significant.

(4) PSR

Reducing patient care effectiveness

As mentioned earlier, the understanding of effectiveness in the healthcare sector relates to the effect of medical intervention in changing the natural history of a particular disease for the better (Cochrane, 1972, cit. in Burches & Burches, 2020, p. 2). Following the growing importance of ICTs to support or enhance health and healthcare systems, expectations have recently been tempered due to the publication of studies that emphasize the lack of knowledge on risks, problems, and failures of health ICTs (Guise et al., 2014, p. 2). In this light, the observed risks of ICTs in healthcare regarding telemedicine are related to a lack of effectiveness of care caused by the intervention design, implementation factors, or intrinsic characteristics of the treated groups (Ossebaard, de Bruijn, & Geertsma, 2013, p. 59). Stanberry (2000, cit. in Parimbelli et al., 2018, p. 91) underlined the potential of telemedicine to create new clinical risks and responsibilities, stressing the necessity of better education and guidance for medical professionals about the practical and professional issues that may arise. Finally, Guise et al. (2014, p. 6) revealed a change in the nature of clinical work as a recurring safety issue associated with ICT use. However, the concrete patient safety risks derived from the potential reduced care effectiveness of telemedicine, as for its benefits, remain unclear (Guise et al., 2014, p. 10), an aspect that thus casts some ambiguity on the relationship between observed and latent variables.

Hypothesis 10 (H10): The relationship between the item reduced patient care effectiveness and the latent construct PSR is moderately positive and statistically significant.

Hindering physician–patient relationship

Concerns have arisen for telemedicine based on the principle of distance regarding the modification of the patient–physician relationship (Ekeland et al., 2010, p. 741). Lack of in-person care and hindrances presented by ICT use instead of face-to-face care are the major concerns that result from it (Guise et al., 2014, p. 6). Although it should not be assumed a priori that the application of distant consultations induces a failure of the patient–doctor relationship (in some cases, avoiding face-to-face interaction might even improve the relationship, e.g., in matters concerning sexuality or family problems), important factors such as physical or mental impediments (reduced vision, disabilities), depersonalization due to indirect interaction between patient and physician, different process of consultation (omission to introduce oneself), inability to perform a comprehensive consultation because of the impossibility of conducting a physical consultation, and lack of knowledge or skills have been recognized as central in hindering the relationship between health professional and patient (Hjelm, 2005, pp. 66–67).

Hypothesis 11 (H11): The relationship between the item hindering the physician–patient relationship and the latent construct PSR is strongly positive and statistically significant.

Jeopardizing patient privacy

Privacy is defined as data confidentiality, which means that only authorized users can access it (Alkhater et al., 2014, p. 1042). It is among the most important requirements in eHealth systems, such as telemedicine (Dong et al., 2012, cit. in Jin & Chen, 2015, p. 59). By employing telemedicine, healthcare professionals and patients are connected through wireless communications (Olanrewaju et al., 2013, p. 19) without the possibility of physical control (Jin & Chen, 2015, p. 59), which might increase the potential for security breaches (Mehta, 2014, p. 1015) and the threat of leaking patients' information or causing unauthorized access to medical data (Zulfiqar et al., 2018, p. 7930). Patients may not know exactly who will be responding to and sharing their personal medical information, further raising privacy concerns (Mehta, 2014, p. 1015). Moreover, the ineffective management of privacy issues in telemedicine might compromise the overall success of the health system, threatening hospitals with severe lawsuit costs (Olanrewaju et al., 2013, p. 19). Inappropriate use of personal information by third parties and information leakage in the real world are concerns that decrease one's predisposition to use connected health services, such as telemedicine (Jia et al., 2019, p. 15). Users with high privacy concerns related to the exchange of information within a telemedicine system might therefore be reluctant to adopt it (Kamal et al., 2020, p. 4). However, studies on privacy issues related to telemedicine show that breaches in patient's confidentiality do not constitute a significant risk (i.a., Dünnebeil et al., 2012; Banbury et al., 2018; Ashfaq et al., 2020; Luciano et al., 2020). In their study on physician's perceptions of telemedicine in HIV care provision, Anderson et al. (2017) even concluded that telemedicine utilization can increase patient's privacy. These findings might also mean that users believe that the benefits of telemedicine outweigh the risk of breaching patient's privacy (Luciano et al., 2020, p. 2358). Privacy issues relate, in this sense, more to an operational level rather than an ethical one, meaning that robust privacy and security plans accompanying any telemedicine program might ensure higher confidence (Mehta, 2014, p. 1015).

Hypothesis 12 (H12): The relationship between the item jeopardizing patient privacy and the latent construct PSR is moderately positive and statistically significant.

Bringing psychological harm

Telemedicine is conducive to improved care processes and health status and to declines in worry about timely interventions since both the physiological and physical status of patients can be monitored by healthcare professionals, providing patients with increased feelings of reassurance and close monitoring (Ciere et al., 2012, p. 384). Also, a psychological "safety distance" may help patients to be more open and available (Frank et al., 1997, cit. in Hjelm, 2005, p. 67). However, only a few studies have considered psychological distress caused by telemedicine (Hirani et al., 2017, p. 2), alternatively, with "the perceived threat based on the perception that employing telemedicine services will not yield any mental satisfaction, resulting in psychological discomfort" (Kamal et al., 2020, p. 4). Especially when handling diagnosis and treatment of diseases such as cancer or other long-term conditions, treating clinicians may face important side effects from the physical and psychological viewpoints (Cartwright et al., 2013, p. 2; Larson et al., 2019, p. 2). Anxiety and depression are indicated as typical psychological outcomes affecting a patient's health relating to quality of life and that commonly translate into poorer endpoints such as self-management, disease control, health service use, costs, and mortality (Rodriguez-Artalejo et al., 2005, Ciechanowski et al., 2007, Moussavi et al., 2007, Maurer et al., 2008, and Yohannes et al., 2010, cit in Cartwright et al., 2013, p. 2). In this light, telemedicine has potentially detrimental effects, such as threats to self-care and associated dependency, suggesting that telemedicine can define health problems as something more serious than they felt they were, stereotypically associating them with being very sick, very old, or highly dependent (Sanders et al., 2012, p. 9). Concurrently, while telemedicine seems to discourage patient's self-activation, it also reduces feelings of unworthiness and burden, bringing new ways of engaging with healthcare professionals despite reduced face-to-face contact (A. Rogers et al., 2011, p. 1083). In their systematic review on the effect of telemedicine interventions on usual care for cancer survivors' quality of life, Larson et al. (2019, p. 16) showed that telemedicine has a statistically significant positive impact on the quality of life of patients, and some of the studies indicated improvements in areas such as depression, anxiety, and emotional, social, and physical wellbeing.

Hypothesis 13 (H13): The relationship between the item bringing psychological harm and the latent construct PSR is moderately positive and statistically significant.

Organizational context

(5) CAM

Attitude toward technology-empowered virtual patient care, technology-assisted consultation, and increased use of IT in patient care

Observers analyzing healthcare professionals' general skepticism in using IT-driven systems have identified some barriers to explain their low uptake. While they suggest that telemedicine might be perceived by some physicians as a threat to their expertise (Rho et al., 2014, p. 560), findings from previous studies have indicated that physicians are more unwilling to use technologies in their routine work, as they might find it interfering with their traditional practices (Anderson, 1997, and Anderson & Aydin, 1997, cit. in Chau & Hu, 2002, p. 298). Literacy gap is also conducive to more resistant attitudes toward adoption (Nittas & Von Wyl, 2020, p. 2), despite physicians' thorough general competence and learning capacity. Also, because of their demanding educational and specialized training, physicians are likelier to stick to practices similar to those in which they were trained and/or perform with relatively high autonomy (Chau & Hu, 2002, p. 298). However, some studies also consider physicians' positive attitudes toward telemedicine when specific criteria are satisfied. Among these, accessibility of patients' records and to patients themselves, individual factors such as self-efficacy regarding telemedicine, and regulatory factors—especially incentives—are credited to raise physicians' acceptance of telemedicine (Rho et al., 2014, pp. 560–561). Technical health IT skills and prior experience are likelier to support a long-term commitment to IT use (Ingebrigtsen et al., 2014, p. 400). Based on the findings by Taylor and Todd (1995), Chau and Hu (2002, p. 307) investigated the effect of attitude on physicians' intention to accept telemedicine, performing measurement of the construct based on three items: "using telemedicine technology in patient care and management is a good idea," "using telemedicine technology in patient care and management is unpleasant," and "using telemedicine technology is beneficial to my patient care and management." All items showed desirable measurement convergent validity, accounting for a good fit between the observed and latent variables.

Hypothesis 14 (H14): The relationship between the item attitude toward technology-empowered virtual patient care and the latent construct CAM is strongly positive and statistically significant.

Hypothesis 15 (H15): The relationship between the item attitude toward technology-assisted consultation and the latent CAM is strongly positive and statistically significant.

Hypothesis 16 (H16): The relationship between the item increased use of IT in patient care and the latent construct CAM is strongly positive and statistically significant.

External environment

(6) PSN

Unmet patient service needs

Unmet service needs are defined as those services that individuals report needing but are not currently receiving (Calsyn & Winter, 2001, p. 157). Among such services, Galushko et al. (2014, p. 276) identified, for instance, several different types of patients' unmet demands, such as access to services, competence, treatment options, physician–patient interaction, adequate time devoted to consultation, coordination and continuity of services and financing. Although some of these needs are suggested to be met by telemedicine, as for providing easier access to medical services (especially in rural areas) (Committee on Evaluating Clinical Applications of Telemedicine, 1996, p. 18) or, to some extent, telemedicine's cost effects (Ekeland et al., 2010), prior research has shown that employing a certain service utilization does not automatically induce the conclusion that needs are actually met (Lefebvre et al., 2000, p. 69).

Hypothesis 17 (H17): The relationship between the item unmet patient service needs and the latent construct PSN is positive and statistically significant, while the magnitude of the association is expected to be low.

Existing service gap

The notion of service gap retraces the works of Parasuraman et al. (1988) who developed a model illustrating how consumers evaluate quality by considering the factors that matter in determining quality; by developing the so-called "Gap Model," the authors identified the possible reasons causing a gap between expected and perceived quality (Mauri et al., 2013, p. 136). In their systematization, Parasuraman et al. (1988) identified five gaps of which the "Customer Gap" is considered the main one, indicating the discrepancy between users' expectations and the actual delivery of the service (Mauri et al., 2013, p. 136). Following the rising healthcare costs, increasing demands of patients and requests for universal access to care, telemedicine is viewed as a solution to tackle these challenges (Luciano et al., 2020, p. 2345). However, as outlined by P. J.-H. Hu et al. (2002, p. 216), service positioning is critical when considering telemedicine adoption; that is, the targeted service needs to be properly positioned regarding the existing services, market segment, and competing services in assessing the organization's service needs. For instance, an early analysis of perceived service gaps of telemedicine services in US rural hospitals showed surprisingly low rates, suggesting that the current services were already viewed as adequate in addressing the perceived needs (Wakefield et al., 1997, p. 61). Overall, however, the fit between the two variables appears to be well founded.

Hypothesis 18 (H18): The relationship between the item existing service gap and the latent construct PSN is strongly positive and statistically significant.

TECHNOLOGICAL CONTEXT	
PEOU	PEOU1: Easy to become skillful in using telemedicine
	PEOU2: Finding the telemedicine flexible to interact with
PTS	PTS1: Telemedicine certification by related government authority
	PTS2: Telemedicine endorsement by medical professional societies
PSB	PSB1: Improving the timeliness of patient care
	PSB2: Reducing patient care and service costs
	PSB3: Improving service productivity of medical staff
	PSB4: Reducing unnecessary patient transfers or admissions
	PSB5: Improving overall effectiveness of patient care
PSR	PSR1: Hindering physician–patient relationship
	PSR2: Reducing patient care effectiveness
	PSR3: Jeopardizing patient privacy
	PSR4: Bringing psychological harm
ORGANIZATIONAL CONTEXT	
CAM	CAMS1: Collective attitude toward telemedicine-empowered virtual patient care
	CAMS2: Collective attitude toward technology assisted consultation
	CAMS3: Collective attitude toward increased use of IT in patient care
ENVIRONMENTAL CONTEXT	
PSN	PSN1: Unmet patient service needs
	PSN2: Existing service gap

Table 1: Overview of the latent variables and their observed variables (Hu et al., 2002; own representation)

5.2 Specification of the measurement model

When translating the measurement model into a statistical form, which specifies the relations between latent and observed variables, such as postulated in the measurement hypotheses, some considerations are applied to CFA specifically based on parameter constraints. CFA requires some restrictions on the patterns of factor loadings; factor loadings are fixed to zero for indicators that do not measure the factor for which a relationship is hypothesized (Hoyle, 2000, p. 468). This converts statistically into the following statistical model:

(Eq. 1) $$X = \Lambda\xi + \epsilon,$$

where X represents the observed variables, ξ are the latent variables, and Λ is a matrix containing the factor loadings λ_{ij}, some of them being fixed at zero, as specified earlier. ϵ represents the error.

The concept of identification is also crucial in specifying the measurement model. Identification addresses the question of whether it is possible to determine unique estimates for a set of observed variables or, alternatively, whether the factor loadings are functions only of the observed variables (Bollen, 1989, p. 88). If a unique solution for the parameters can be found, then the model is considered to be identified and therefore testable; otherwise, one or more parameters are unidentified, which means that they are subject to arbitrariness and thus might take on different values to define the same model, which makes an empirical evaluation of the model not possible (Byrne, 2010, p. 33). Linked to the issue of identification is the requirement that every latent variable has its scale determined (Byrne, 2010, p. 34). To achieve identification and satisfy the scaling requisite, one of the factor loadings per set of items is fixed to one (Byrne, 2010, p. 35). Graphically, the postulated relationships are represented in the following path diagram.

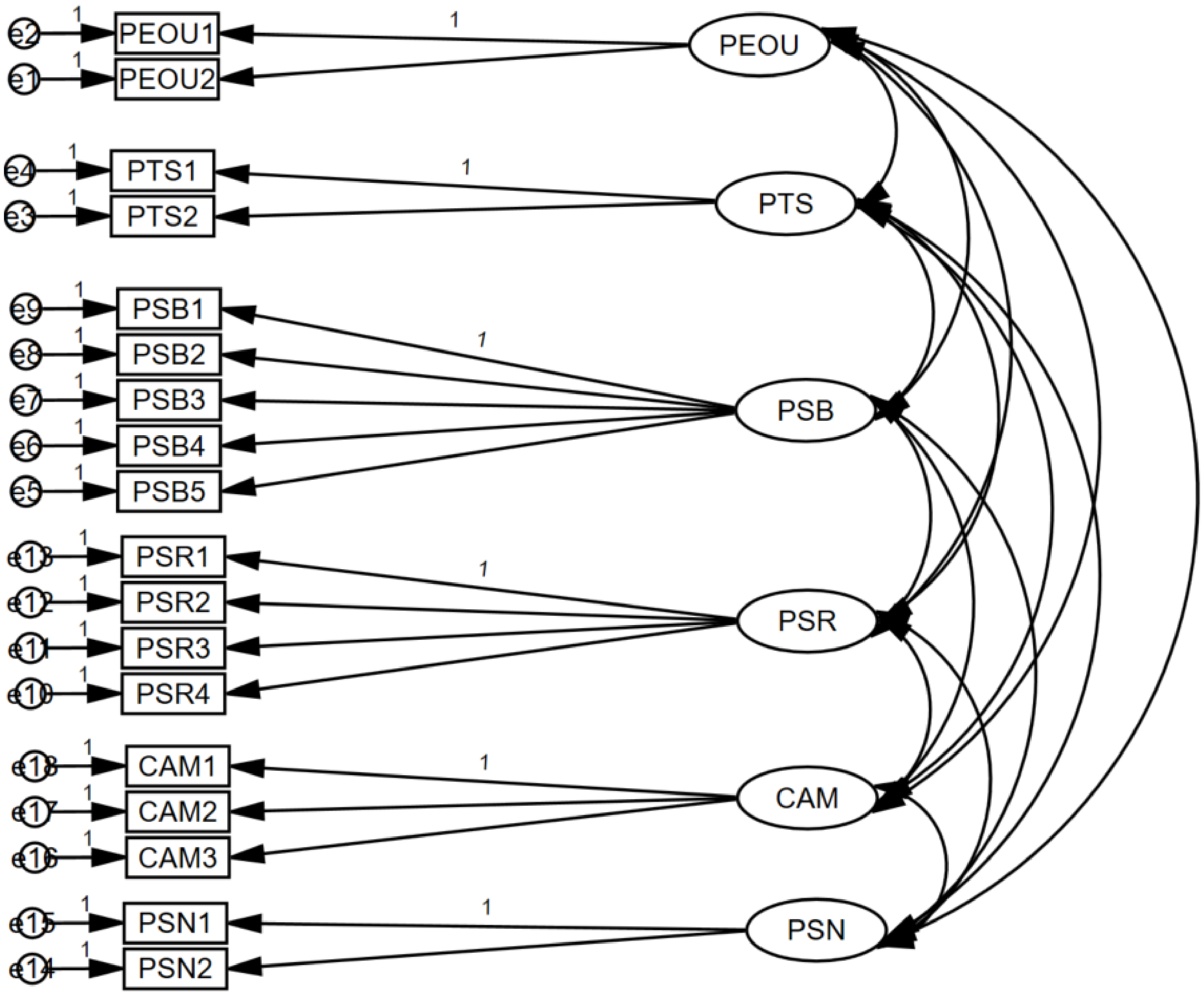

Figure 4: Measurement model representation (AMOS output)

Therefore, the CFA model represented in Figure 4 summarizes the a priori hypotheses as follows:

- Telemedicine adoption can be explained by six factors: PEOU, PTS, PSB, PSR, CAM, and PSN;
- Each set of observed variables (items) has a zero loading on all other factors (non-target loadings) and a nonzero loading on the respective factor that it is designed to measure (target loading);
- The six factors are correlated;
- Errors associated with each item are uncorrelated.

5.3 Methods, data collection, and descriptive statistics

CFA was conducted using the statistical software SPSS and AMOS to verify the measurement quality of each latent construct using the maximum likelihood estimation method. Data were collected by administering an online questionnaire through an identified contact person within each participating organization. Since the findings of the Swiss eHealth barometer suggested a predominant focus on the clinical services of telemedicine in Switzerland (gfs. Bern, 2020, p. 26), these were targeted in the questionnaire rather than other telemedicine activities, such as service collaboration, service delivery, or information exchange, similar to P. J.-H. Hu et al. (2002, p. 205). The questionnaire was written in English and comprised three sections. The first section gathered data on the degree of telemedicine adoption on an adoption continuum of seven logical and distinct phases. The second comprised seven questions aiming at gathering the respondent's perceptions on telemedicine's ease of use, technological safety, benefits, risks, collective attitude, and service needs. Each factor was associated with its respective observed variable, for a total of 18 items measured on a 7-point-Likert scale. The third group gathered information on the socio-demographic characteristics of the participants. A definition of telemedicine was given both at the beginning and throughout the whole questionnaire. The extract from the questionnaire can be viewed in Appendix 1. All Swiss cantonal and university hospitals were contacted to participate in the questionnaire. The choice to target only public healthcare organizations is multifaceted. First, the position of public healthcare organizations is not purely based on economic criteria but encompasses socio-political ones, thereby allowing hospitals to considerably perform preliminary work and make resources available for the emergence of new and superordinate activities for which a return on investment is not necessarily given in a classic economic understanding, but the result is expected to benefit the entirety (Carigiet & Franz, 2013, p. 244). The choice was therefore also motivated by the likelihood of public hospitals' involvement in adopting telemedicine, cantonal healthcare organizations representing, together with university hospitals, a considerable part of general hospitals, which are publicly financed or subsidized for about two-thirds (TRISAN, 2019, pp. 37–38). The questionnaire was provided to an identified contact person and then administered by the latter to as many physicians affiliated with the organization as possible. As discussed, a crucial factor for telemedicine adoption is the attitude of healthcare professionals on the ground, which is the way this specific group was targeted (Zanaboni & Wootton, 2012, p. n.p.). Respondents were given approximately four weeks between the end of December 2020 and February 2021 to complete the questionnaire. Late responders were given two additional weeks, extending the observational period from December 29, 2020 to February 21, 2021.

Overall, 135 responses were returned from the survey[1]. After performing database cleanup of missing data and incomplete responses, the resulting sample was 77 respondents. Missing values were treated as suggested by Carter (2006, cit. in Dastgeer et al., 2012, p. 69) and were deleted or imputed into the dataset accordingly. Sample size plays a critical role in estimating and interpreting the results when conducting this analysis (Hair et al., 2006, cit. in Dastgeer et al., 2012, p. 68). Although no standard requirement of sample size for SEM exists, researchers have argued that the absolute minimum sample size must at least exceed the number of correlations in the input data matrix, thus recommending a minimum ratio of at least five respondents for each estimated parameter, with a ratio of ten respondents per parameter considered most appropriate (Reisinger & Mavondo, 2007, Schreiber et al., 2006, AND Hair et al., 2006, cit. in Dastgeer et al., 2012, p. 68). This translated in this case to a recommended minimum sample size of $5 \times 18 = 90$. Hence, with a sample size of 77, the present analysis did not fulfill the basic requirements suggested by the literature. However, in a study investigating the sample size requirements for SEM, Wolf et al. (2013, pp. 925–926) demonstrated broad variability in sample size requirements depending on the models, indicating that sample size requirements decreased when the number of indicators of a factor increased, especially when having three to four indicators per factor—a finding that is also corroborated by prior studies suggesting that increasing the number of indicators per factor may be one way to compensate for a general small sample size (Marsh et al., 1998, cit. in Wolf et al., 2013, p. 926).

Table 2 overviews the respondents' demographic profile. Most of the respondents were male (65.8%) and 35 years of age and older, a finding confirmed by the predominant hierarchical

[1] The mailing of the questionnaire was managed by an external informant, and it was not possible to calculate the response rate for all the organizations surveyed, which is why this information is missing from the present study.

position held by participants, that of chief physician (32.0%) or lead physician (29.3%)—a position that usually depends on the years of experience. The majority of the respondents (59.7%) indicated that they attended medical school in Switzerland, and a substantial percentage (23.4%) reported that they had graduated from a German medical school.

		Frequency	%
Gender	Male	50	65.8%
	Female	24	31.6%
	non-binary / third gender	0	0.0%
	I prefer not to say	2	2.6%
Age	18–24	0	0.0%
	25–34	9	12.0%
	35–44	25	33.3%
	45–54	19	25.3%
	55–64	21	28.0%
	65+	1	1.3%
Country of attendance of medical school		1	1.3%
	Austria	3	3.9%
	Belgium	2	2.6%
	France	3	3.9%
	Germany	18	23.4%
	Italy	2	2.6%
	Romania	1	1.3%
	Spain	1	1.3%
	Switzerland	46	59.7%
Hierarchical position held at the organization	Hospital executive officer	1	1.3%
	Medical director	1	1.3%
	Assistant medical director	0	0.0%
	Chief physician	24	32.0%
	Lead physician	22	29.3%
	Head of Clinic	17	22.7%
	Assistant doctor	8	10.7%
	Other	2	2.7%

Table 2: Summary of respondents' profile (SPSS output)

Respondents were also asked about their medical specialty. Figure 5 shows the distribution of the different specialty areas: among the 24 specialties represented by the collected data, internal medicine constituted the most represented area (20%), followed at a distance by gynecology and obstetrics, anesthesiology, and orthopedics and traumatology (9.1%).

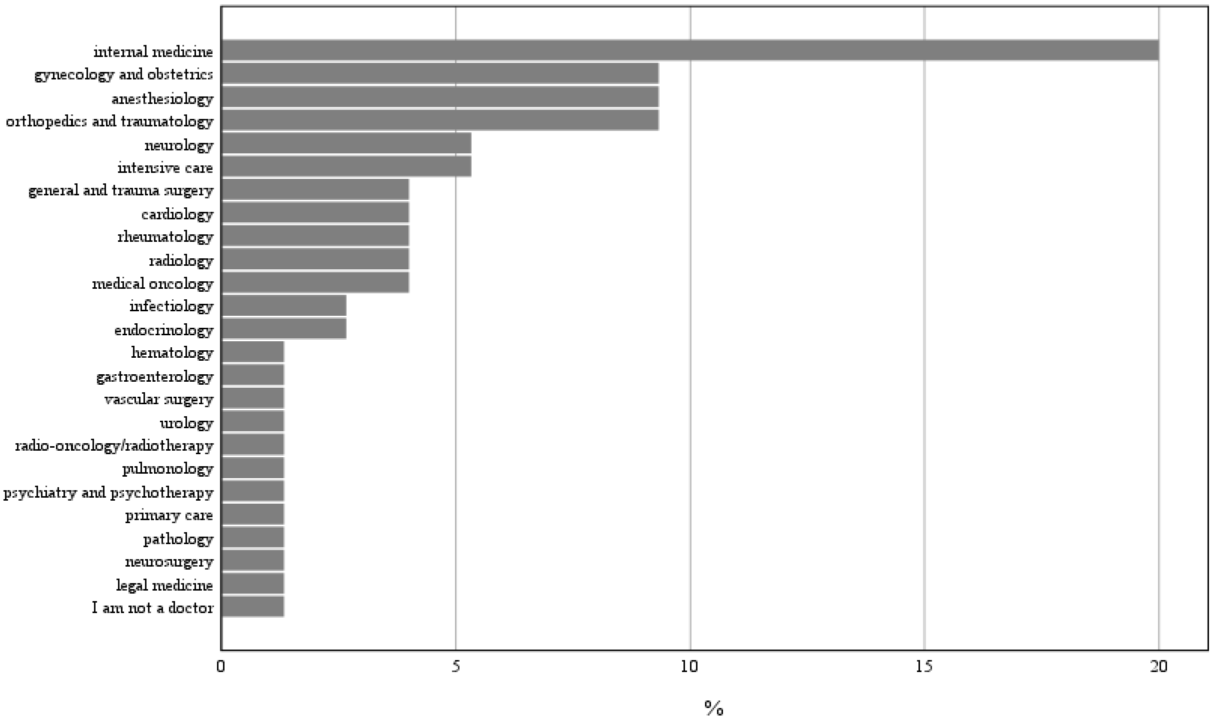

Figure 5: Distribution of medical specialties (SPSS output)

Table 3 overviews the participating healthcare organizations' features. In total, 15 organizations from all the different Swiss regions engaged in the investigation (the Canton AG counts two cantonal hospitals). Although the distribution does not perfectly reflect the Swiss hospital landscape (e.g., smaller hospitals are overrepresented compared to larger hospitals), these responses reflect the regional and linguistic representation of the country. Finally, 77.3% were cantonal hospitals, and 21.3% were university hospitals.

		Frequency	%
Location of healthcare organization (Canton)	AG	10	13,3%
	BE	2	2,7%
	BL	1	1,3%
	GE	2	2,7%
	GR	2	2,7%
	JU	2	2,7%
	LU	1	1,3%
	OW	4	5,3%
	TI	3	4,0%
	UR	8	10,7%
	VD	14	18,7%
	VS	3	4,0%
	ZG	22	29,3%
	ZH	1	1,3%
Legal status of healthcare organization	Cantonal hospital	58	77,3%
	University hospital	16	21,3%
	Other	1	1,3%

Table 3: Summary of healthcare organizations' profile (SPSS output)

5.4 Data analysis

5.4.1 Preliminary testing

Before undertaking CFA, some preliminary testing was performed. When using the maximum likelihood estimation method to conduct CFA, multivariate normality is required (Alhija, 2010, p. 164). Normality was jointly tested using both the Kolmogorov–Smirnov and the Shapiro–Wilk tests, the latter preferred for being likelier to detect non-normality in smaller samples (< 100), such as in this case (Samuels & Marshall, 2012, n.p.). The null hypothesis that data is normally distributed was rejected across all variables, the tests suggesting strong evidence of non-normality. The results of normality testing are presented in Appendix 2. With data revealing evidence of non-normality, interpretations based on the usual maximum likelihood estimation method may be problematic (Byrne, 2010, p. 105). As possible solutions, the literature suggests utilizing alternative methods of estimation, such as asymptotic distribution free estimation (ADF) (Byrne, 2010, p. 105). Nonetheless, ADF is well known to perform better with large samples (1,000–5,000) and is therefore not suitable for the present case; numerous other authors have suggested that it might be more appropriate to correct the test statistic rather than use a different mode of estimation (i.a., Chou et al., 1991, and Hu et al., 1992, cit in Byrne, 2010, p. 105). The Satorra–Bentler test statistics is often cited as a useful instrument when distributional assumptions are violated; however, this method is unavailable in the AMOS program (Byrne, 2010, p. 105). One suggested approach to handling multivariate non-normal data in AMOS is therefore to use the bootstrapping procedure (i.a., West et al., 1995, Yung & Bentler, 1996, and Zhu, 1997, cit. in Byrne 2010, p. 330). The key idea behind bootstrapping is that it enables the creation of multiple subsamples from an original database (Byrne, 2010, p. 331). Through this resampling technique, the original sample is considered to represent the population, and multiple subsamples of the same size as the main one are then drawn randomly with replacements from this population and provide the data for empirical investigation of the variability of parameter estimates and indices of fit (Byrne, 2010, pp. 330–331). Since bootstrapping is found to assess the stability of the estimates and therefore account for their values with greater accuracy (Byrne, 2010, p. 332), the procedure was applied when performing CFA in AMOS using the Bollen–Stine bootstrap, as it is found to have good accuracy and efficiency in recovering the estimates—especially when estimating the measurement model (Sharma & Kim, 2013, p. 207). Next, multicollinearity was tested. Multicollinearity arises when two or more variables are so highly correlated that they both basically represent the same underlying construct (Byrne, 2010, p. 168). As a general rule of thumb, variance inflation factors (VIFs) exceeding 10 are signs of serious multicollinearity requiring correction (Schreiber-Gregory & Bader, 2018, p. 3). Only the two variables, CAM 1 and CAM2, show values higher than 4 but still range well below 10. Appendix 3 presents the results of the multicollinearity test.

5.4.2 Results

As a first step, the factor loadings of the observed variables were estimated. Table 4 provides the results for the standardized parameter estimates.

			Estimate	R^2
PEOU1	<---	PEOU	.688	.473
PEOU2	<---	PEOU	.918	.842
PTS1	<---	PTS	.753	.568
PTS2	<---	PTS	.747	.559
PSB1	<---	PSB	.766	.587
PSB2	<---	PSB	.669	.448
PSB3	<---	PSB	.785	.616
PSB4	<---	PSB	.770	.593
PSB5	<---	PSB	.836	.699
PSR1	<---	PSR	.709	.503
PSR2	<---	PSR	.826	.682
PSR3	<---	PSR	.724	.524
PSR4	<---	PSR	.720	.519
CAM1	<---	CAM	.923	.852
CAM2	<---	CAM	.951	.904
CAM3	<---	CAM	.671	.450
PSN1	<---	PSN	.649	.421
PSN2	<---	PSN	.847	.718

Table 4: Standardized parameter estimates of the measurement model (AMOS output)

Standardized factor loadings are interpreted as the correlations between the indicators and their respective factors, whereas the squared standardized factor loading equals the estimate of the amount of the variance of the indicator that is accounted for by the latent construct (R^2). With loadings over .8, the items PEOU2, PSB5, PSR2, PSN2, CAM2, and CAM1 account for very strong correlations. All factor loadings are statistically significant[2]. Ideally, in a CFA, the model should explain the majority of the variance (> 50%) in every indicator (Kline, 2016, p. 301). When considering the R^2, which accounts for the proportions of the explained variance, most of the indicators' variances are explained by the respective factors, except for PEOU1, PSB2, PSN1, and CAM3, which are also the items with the weakest factor loadings. Nonetheless, the

[2] The statistical significance and the standard error are reported for the unstandardized factor loadings in Appendix 4.

overall results showed that the 18 observed variables are appreciably highly and positively correlated with the respective factors. These findings corroborate H2, H14, H15, and H18, which postulated a strongly positive and significant relationship between the items and the respective factor; this is shown by parameters' values over .90 for PEOU2, CAM1, and CAM2, and a value over .80 for PSN2. Likewise, H7, H9, H12, and H13 are confirmed since they postulated a moderately strong and significant relationship, as the findings display parameters' values for PSB3, PSB4, PSR3, and PSR4 between 0.70 and .80. H8 and H17 are also confirmed in that they hypothesized a positive, significant, and weak association, which is evident in their parameters' values for PSB2 and PSN1 under .70. H1, H3 through H5, and H11 were only partially confirmed because despite the significant and positive association, the parameters' values under .8 for PEOU1, PTS1, PTS2, PSB1, and PSR1 just showed a moderate correlation—and not a strong one, as hypothesized. The same logic applies to H6 and H10, which postulated a significant and positive association but were found with an appreciably higher association for PSB5 and PSR2 than expected; vice versa for H16, whose parameters' values for CAM3 were substantially lower than postulated. H6, H10, and H16 can therefore be viewed as the only hypotheses that were not completely corroborated by the results, although they cannot be rejected on this basis. Further discussions of this issue are addressed later in Chapter 7. Table 5 briefly summarizes the conclusions drawn from the results of the formulated hypotheses, showing that none of the measurement hypotheses were rejected:

Hypothesis				Estimate	R^2
H1: partially confirmed	PEOU1	<---	PEOU	.688	.473
H2: confirmed	PEOU2	<---	PEOU	.918	.842
H3: partially confirmed	PTS1	<---	PTS	.753	.568
H4: partially confirmed	PTS2	<---	PTS	.747	.559
H5: partially confirmed	PSB1	<---	PSB	.766	.587
H8: confirmed	PSB2	<---	PSB	.669	.448
H9: confirmed	PSB3	<---	PSB	.785	.616
H7: confirmed	PSB4	<---	PSB	.770	.593
H6: partially confirmed	PSB5	<---	PSB	.836	.699
H11: partially confirmed	PSR1	<---	PSR	.709	.503
H10: partially confirmed	PSR2	<---	PSR	.826	.682
H12: confirmed	PSR3	<---	PSR	.724	.524
H13: confirmed	PSR4	<---	PSR	.720	.519
H14: confirmed	CAM1	<---	CAM	.923	.852
H15: confirmed	CAM2	<---	CAM	.951	.904
H16: partially confirmed	CAM3	<---	CAM	.671	.450
H17: confirmed	PSN1	<---	PSN	.649	.421
H18: confirmed	PSN2	<---	PSN	.847	.718

Table 5: Summary of corroborated or partially confirmed hypotheses (own representation)

Analyzing the standardized parameter estimates (correlations) allows to test both convergent and discriminant validity, two interlocking propositions that are key when trying to assess construct validity. While construct validity reflects the extent to which the measurements used really test the hypothesis or theory they are measuring (Ginty, 2013, n.p.), convergent validity examines the extent to which the indicators capture a common construct (Carlson & Herdman, 2012, p. 18), therefore analyzing whether the relation postulated between the indicators and the construct actually exists. The precise level of association necessary to account as “highly” correlated is undefined since most convergent validities in real research reside between 0 and 1; however, as a general rule of thumb, loadings of .70 or higher commonly indicate converging measures (Carlson & Herdman, 2012, p. 18). Except for some slightly lower values for PEOU1, PSB2, PSN1, and CAM3, the estimates reported in Table 4 account for fairly good convergent validity. Convergent validity can also be calculated using the average variance extracted (AVE), which results as the ratio between the sum of the squared standardized loadings and the number of indicators per factor; by taking a value of .5 or more, the AVE is considered acceptable and therefore accounts for convergent validity (Fornell & Larcker, 1981, p. 46). Discriminant validity verifies that each factor represents a separate dimension and therefore appears when no two constructs are highly correlated; it is calculated as the square root of AVE and is considered acceptable when the inter-factor correlations are less than the square root of AVE (Fornell & Larcker, 1981, p. 46) or, as a general rule of thumb, when taking values under .85 (Kline, 2011, cit. in Hamid & Sidek, 2017, p. 3). Table 6 summarizes the results for AVE and the square root of AVE:

<table>
<tr><th colspan="3"></th><th>Convergent validity (AVE)</th><th>Discriminant validity ($\sqrt{AVE}$)</th></tr>
<tr><td>PEOU2</td><td><---</td><td>PEOU</td><td rowspan="2">.658</td><td rowspan="2">.811</td></tr>
<tr><td>PEOU1</td><td><---</td><td>PEOU</td></tr>
<tr><td>PSB5</td><td><---</td><td>PSB</td><td rowspan="5">.589</td><td rowspan="5">.767</td></tr>
<tr><td>PSB4</td><td><---</td><td>PSB</td></tr>
<tr><td>PSB3</td><td><---</td><td>PSB</td></tr>
<tr><td>PSB2</td><td><---</td><td>PSB</td></tr>
<tr><td>PSB1</td><td><---</td><td>PSB</td></tr>
<tr><td>PSR4</td><td><---</td><td>PSR</td><td rowspan="4">.557</td><td rowspan="4">.746</td></tr>
<tr><td>PSR3</td><td><---</td><td>PSR</td></tr>
<tr><td>PSR2</td><td><---</td><td>PSR</td></tr>
<tr><td>PSR1</td><td><---</td><td>PSR</td></tr>
<tr><td>PSN2</td><td><---</td><td>PSN</td><td rowspan="2">.570</td><td rowspan="2">.755</td></tr>
<tr><td>PSN1</td><td><---</td><td>PSN</td></tr>
<tr><td>CAM3</td><td><---</td><td>CAM</td><td rowspan="3">.735</td><td rowspan="3">.858</td></tr>
<tr><td>CAM2</td><td><---</td><td>CAM</td></tr>
<tr><td>CAM1</td><td><---</td><td>CAM</td></tr>
<tr><td>PTS1</td><td><---</td><td>PTS</td><td rowspan="2">.564</td><td rowspan="2">.751</td></tr>
<tr><td>PTS2</td><td><---</td><td>PTS</td></tr>
</table>

Table 6: Results for convergent and discriminant validity (own calculation and representation)

The results shown in Table 6 account for good convergent validity, with values over .50 for all measures, as well as for discriminant validity, which, except the set concerning CAM, takes values under .85. The excess for CAM was, however, small enough (.008) to be ignored, as suggested by Hamid & Sidek (2017, p. 4).

Next, the model fit, e.g., the goodness-of-fit between the hypothesized model and the sample data (Byrne, 2010, p. 70) was assessed. This is usually performed by running several statistical tests, the most common being the *likelihood ratio-based chi-square test* (LR chi-square test) (Shi et al., 2018, p. 676). The chi-square test specifies the amount of difference between expected and observed covariance matrices, with a chi-square value close to zero indicating little difference between the expected and observed covariance matrices; also, the probability level must exceed .05 when the chi-square is close to zero (Suhr, 2006, p. 1). The chi-square test's null hypothesis is, therefore, that the predicted model and the observed data are equal—a null hypothesis that, unlike traditional procedures, is hoped *not* to be rejected (Byrne, 2010, p. 70). The estimation of the measurement model resulted in an overall chi-squared value of 170.541 with 121 degrees of freedom and a probability level of .002, therefore suggesting a rejection of the null hypothesis and thus a bad model fit. However, in most empirical situations, the considered model is, to some degree, misspecified (Box, 1979, and MacCallum, 2003, cit. in Shi et al., 2018, 676), which causes the LR chi-square test to indicate an unacceptable fit, even when the model misspecification is relatively minor (Shi et al., 2018, p. 676). Hence, the chi-square test is mostly intended as a quick overview of the model fit, and the literature suggests performing other statistical tests besides the LR chi-square test to assess model-data fit (Byrne, 2010, p. 70). Fit-statistics can be divided into two categories: while *model-fit statistics* are generally chi-square statistics designated to support or reject the null hypothesis stating that the researchers' model is correct ("exact-fit" hypothesis), *approximate fit* indexes are not significance tests, meaning that they act as continuous measures of model-data correspondence (Kline, 2016, pp. 265–266). Approximate fit indexes can be in turn divided into four categories: a) absolute fit indexes measure how well an a priori model—the researcher's one—explains the data; b) incremental/relative fit indexes measure the relative improvement of fit of the researcher's model compared to a baseline; c) parsimony-adjusted indexes incorporate in their formulas a correction or "penalty" for model complexity and, respectively, "reward" for model parsimony; and d) predictive fit indexes estimate model fit in hypothetical replication samples of the same size and randomly selected from the same population as the original sample, therefore basing on population rather than on sample (Kline, 2016, pp. 265–266). As fit statistics are rather numerous, the choice of which test to conduct was restricted to the following set of recommended tests suggested by Kline (2016, p. 269):

- The *root mean square error of approximation* (RMSEA) is an absolute fit index that assesses how well the model fits the populations covariance matrix (Byrne, 1998, cit. in Hooper et al., 2008, p. 54). RMSEA is sensitive to the number of estimated parameters in the model and therefore favors parsimony by choosing the model with the lesser number of parameters (Hooper et al., 2008, p. 54). RMSEA ranges from 0 to 1, with a smaller value indicating better model fit; acceptable model fit assumes a RMSEA value of .06 or less (L. Hu & Bentler, 1999, cit. in Suhr, 2006, p. 2).

- The *comparative fit index* (CFI) is an incremental fit index representing the discrepancy function adjusted for the sample size; CFI is found to perform well when the sample size is small, as in the present case (Tabachnick and Fidell, 2007, cit. in Hooper et al., 2008, p. 55). CFI ranges from 0 to 1, with a larger value indicating better model fit; acceptable model fit assumes a CFI value of 0.9 or greater (L. Hu & Bentler, 1999, cit in Suhr, 2006, p. 2).
- Finally, the *standardized root mean square residual* (SRMR) is an absolute fit index representing the average standardized residual covariance, with values close to 0.08 or less being indicative of an acceptable model (L. Hu & Bentler, 1999, p. 27)—a perfect model fit would be indicated by RMR = 0. AMOS does not provide a tabular output for SRMR; however, it has a macro that displays the results when running the analysis.

Table 7 summarizes the results for the abovementioned goodness-of-fit statistics.

RMSEA

Model	RMSEA
Default model	.073
Independence model	.255

CFI

Model	CFI
Default model	.934
Saturated model	1.000
Independence model	.000

SRMR

Model	SRMR
Default model	.0683

Table 7: Assessment of model fit using selected approximate fit indexes (adapted AMOS output, own representation)

For each set of statistics, up to three types of models are reported, with the default model representing the model under scrutiny; the independence and the saturated model correspond to two extremes where the variables are either completely independent or, respectively, the number of estimated parameters equals the number of data points (Byrne, 2010, p. 74). The independence model usually acts as the baseline model for incremental fit indexes (Kline, 2016, p. 267). When comparing the resulting values with the cutoff values suggested by the literature, a good model fit can be assessed across all indexes, except for RMSEA, which showed a value of .073 slightly over the acceptable level of .06. However, some authors have argued that values as high as .08 represent reasonable errors of approximation in the population and can therefore be considered acceptable (Browne & Cudeck, 1993, cit. in Byrne, 2010, p. 80), especially in small samples, where the RMSEA tends to over-reject true population models (Byrne, 2010, p. 80). Based on the goodness-of-fit statistics, a good fit of the hypothesized six-factor CFA model with the sample data was suggested.

6. FACTOR SCORE PATH ANALYSIS

6.1 Operationalization of the dependent variable

The adoption and diffusion process can be deemed to have the broad characteristics of a developmental theory, where change is relatively slow and structured; most adoption theories therefore consider technology adoption regarding stages, although not necessarily clear-cut, which in turn suggest a progression about knowledge and understanding (Straub, 2009, p. 641). Operationalization of the dependent variable “organizational technology adoption” followed P. J.-H. Hu et al.’s (2002, p. 206) process-oriented view on technology adoption assessment, where an adoption continuum of seven logical and distinct phases corresponds to the specific stages in which organizations are currently located in the adoption process (1 = technology not adopted; 7 = technology adopted). Each phase expresses the likelihood that an organization will adopt telemedicine technology: the later into the adoption stage, the higher the adoption likelihood.

1. Thought about potential adoption but decided not to pursue at present time
2. Informally discussed potential adoption but have taken no concrete actions
3. Have designated a task force or individuals to investigate potential adoption
4. Have or are about to complete adoption plan to be submitted to a funding agency
5. Have put together a formal proposal that is currently under external review
6. Have located and secured financial resources and technology source
7. Already adopted telemedicine technology and used it for clinical purposes

Table 8: Operationalization of dependent variable “technology adoption”

6.2 Structural hypotheses

(1) PEOU

PEOU reflects the degree to which a person believes that using a particular technology is free of effort (Lin, 2013, p. 244). As outlined by Whitten and Mackert (2005, pp. 519–520), the PEOU of the technology for healthcare providers drives telemedicine adoption. Once an organization engages in the technology adoption process, PEOU might become crucial to the ultimate adoption decision: a technology that is difficult to use or operate is unlikely to be well received by physicians, which is why the evaluation of physicians’ perceptions or assessments of the ease of use are pivotal to adoption (P. J.-H. Hu et al., 2002, p. 202). In their study challenging the concept of PEOU, Lippert and Forman (2005) suggested perceived usefulness to be more important than PEOU. In their investigation on the factors affecting post-adoption behavior of first-tier supply chain members within the U.S. automotive industry toward a new information technology, the authors found perceived usefulness to have a positive, strong and significant impact on the individual's perception of the technology's performance (Lippert & Forman, 2005, p. 374). Moreover, PEOU has been found to exhibit a less consistent effect on intention across conducted studies than perceived usefulness (Lin, 2013, p. 244). However, an understanding of individual judgment of usefulness is still lacking, which is why ease of use is still more popular in usability studies (Straub, 2009, p. 643). Building on P. J.-H. Hu et al.'s (2002, p. 213–214) findings, PEOU is believed to negatively affect technology adoption, suggesting that organizations in advanced adoption phases seem not to consider PEOU as important as organizations in preliminary phases. The direction of the effect is believed to be found in the present study also since organizations are expected to be much more into adoption, triggered by the COVID-19 pandemic.

Hypothesis 19 (H19): PEOU has a significant and negative effect on telemedicine adoption.

(2) PTS

When applied to the healthcare sector, the concept of technological safety can be summarized by the key principle of physicians' practices to "do no harm" (P. J.-H. Hu et al., 2002, p. 202). In the field of telemedicine, concerns around technological safety are paramount to adopters; moreover, not only is the technical safety of the technology itself at interest but also its security regarding reliability, that is, "the level of security procedures in place to protect information or the system from unauthorized access or any other security events" (Alkhater et al., 2014, p. 1042). In the healthcare sector, safety often prevails over security, although both concepts converge once human lives are endangered. Security is therefore a built-in function that manufacturers obey to ensure technological safety (ENISA, 2018, p. 5). In their systematic review of 58 journal articles about telemedicine security in the field of chronic illness, Garg and Brewer (2011, p. 773) reported a lack of standardization in telemedicine security across all chronic illnesses under study, indicating that many telemedicine researchers are unfamiliar with the field of security in general. As argued by P. J.-H. Hu et al. (2002, p. 202), physicians are, to varying degrees, wary about the safety of the equipment and technology they employ for patient care and services. Poor security may be conductive to lower quality of care and lack of confidence in the services for both providers and consumers (Garg & Brewer, 2011, p. 767) and therefore be a barrier to adoption.

Hypothesis 20 (H20): PTS has a significant and positive effect on telemedicine adoption.

(3) PSB

Similar to the concepts of relative advantages found in E. M. Rogers' diffusion of innovation theory (DOI) and Davis' perceived usefulness, PSB refers "to the degree to which telemedicine technology is perceived as being better than or superior to existing service arrangements" (P. J.-H. Hu et al., 2002, p. 203). Physicians are unlikely to be persuaded of the value of telemedicine unless its technical feasibility is supplemented by medical or service validity (Tanriverdi & Iacono, 1998, cit. in Hu et al., 2002, p. 203). Successful adoption of telemedicine into routine practice occurs when it is perceived as a benefit to medical or health-related issues (Obstfelder et al., 2007, n.p.).

Hypothesis 21 (H21): PSB has a significant and positive effect on telemedicine adoption.

(4) PSR

As opposed to the perceived benefits provided by telemedicine, healthcare organizations are also constantly concerned about the risks of a new technology (P. J.-H. Hu et al., 2002, p. 203). Trust in and trustworthiness of eHealth initiatives are therefore affected by (perceived) risks (Ossebaard, de Bruijn, van Gemert-Pijnen, et al., 2013, p. 11). Risk refers here to the "combination of the probability of occurrence of harm and the severity of that harm" (ISO/IEC,1999, cit. in Ossebaard et al., 2013, p. 12). This applies in particular when considering service efficacy, outcome effectiveness, physician–patient relationships, and patient (information) privacy (P. J.-H. Hu et al., 2002, p. 203).

Hypothesis 22 (H22): PSR has a significant and negative effect on telemedicine adoption.

(5) CAM

Since physicians are the most important users of telemedicine technology, their attitudes toward the technology and the services it provides are believed to largely determine the readiness of an organization for technology adoption (Hu et al., 2002, p. 203) and therefore for its success (Rho et al., 2014, p. 560). Physicians act as gatekeepers of telemedicine by deciding whether to proactively use it (Whitten & Mackert, 2005, p. 520). Prior research has shown that favorable attitudes are likelier to be associated with a higher level of technology adoption (i.a., Chau & Hu, 2002; Paré et al., 2006).

Hypothesis 23 (H23): CAM has a significant and positive effect on telemedicine adoption.

(6) PSN

Perceived needs relate to an individual's personal judgment about the necessity or benefits of a particular service (Coulton & Frost, 1982, cit. in Cohen-Mansfield & Frank, 2008, p. 507), regardless of whether they are currently receiving any services aimed at meeting those needs (Calsyn & Winter, 2001, p. 157). As argued by P. J.-H. Hu et al. (2002, p. 204), in many cases, the adoption of a new technology is driven by existing needs rather than pushed by the technology itself. Also, since a healthcare organization's primary purpose is to provide services to those in demand, the organization is therefore supposed to explore and evaluate alternative ways of delivering healthcare if existing solutions do not meet service demands regarding service access or quality (P. J.-H. Hu et al., 2002, p. 204). Perceived need assessments relating to self-reported usage or potential usage of services (Calsyn & Winter, 2001, p. 157) is therefore a key step in planning a successful implementation of telemedicine within an organization.

Hypothesis 24 (H24): PSN significantly positively affects telemedicine adoption.

6.3 Specification of the structural model

Path analysis involves employing multiple regressions about formulated causal models and can therefore be translated into linear equations (Mueller, 1996, p. 22). Statistically, the model is converted into the following form:

(Eq. 2) $$Y = \alpha + BY + \Gamma X + \xi,$$

where Y represents the endogenous (dependent) variable "adoption," X is a column vector of the six exogenous (independent) variables, and α represents the intercept. B is a matrix of structural coefficients from endogenous to other endogenous variables, while Γ is a matrix of structural coefficients from the exogenous to the endogenous variables; ξ represents a column vector of error terms of the endogenous variables.

6.4 Methods, data collection, and descriptive statistics

Despite SEM being usually the preferred method to investigate the relationship among latent variables, it also presents the drawback of requiring a large sample size, especially if the model is complex (Schumacker & Lomax, 1996, and Valluzzi, Larson, & Miller, 2003, cit. in Devlieger & Rosseel, 2017, p. 31). Samples of less than 100 cases, such as the present one, are often classified as untenable (Kline, 2011, cit. in Kelcey, 2019, p. 83). Furthermore, since SEM estimates all parameters simultaneously, one misspecification in the model could influence other parts or even the whole model (Devlieger & Rosseel, 2017, p. 31). To overcome the issue of the sample size, prior research has tended to employ the two-step factor score path analysis (FSPA) approach, which allows breaking down the equations by first performing a factor analysis to calculate the factor score for each latent variable and then estimating a path analysis using the factor scores predicted by the measurement model (Kelcey, 2019, p. 84). This second step entails utilizing factor scores in a linear regression, as if they were the true latent variables' scores; hence, one can ensure that the number of the model does not converge (Devlieger & Rosseel, 2017, p. 31). To proceed with the FSPA outlined above, the estimators were calculated. To do so, the factor scores for all latent variables were determined by computing the factor score weights resulting from the AMOS output in SPSS. The computed factor scores were then added to the existing dataset as new variables, accounting for latent variables' scores. The same dataset was used to perform the FSPA.

Adding to the demographic characteristics outlined in Chapter 5.3, respondents were also asked whether they found themselves making more use of telemedicine during the COVID-19 pandemic. This question helped define the historical context and its importance, as it allowed to take a snapshot of the situation at the moment of the investigation. As displayed in Table 9, responses split down the middle, with 48% of respondents stating that they made more use of telemedicine during the pandemic and 49% declaring that they did not make more use of the technology, suggesting that half of the respondents were likeliest influenced by the pandemic in increasing their use of telemedicine.

		%
During the COVID-19 pandemic, I made significantly more use of telemedicine	Yes	48,0%
	No	49,3%
	I don't know	2,7%

Table 9: Frequency table of respondents' telemedicine use during COVID-19

Considering the distribution of the dependent variable "adoption," a clear concentration of data at the extremes is displayed, meaning that most respondents fell between organizations that had already adopted and were implementing telemedicine and those that had not. Figure 7 illustrates the distribution of the dependent variable "adoption," including the curve of normality, which clearly shows a non-normal distribution.

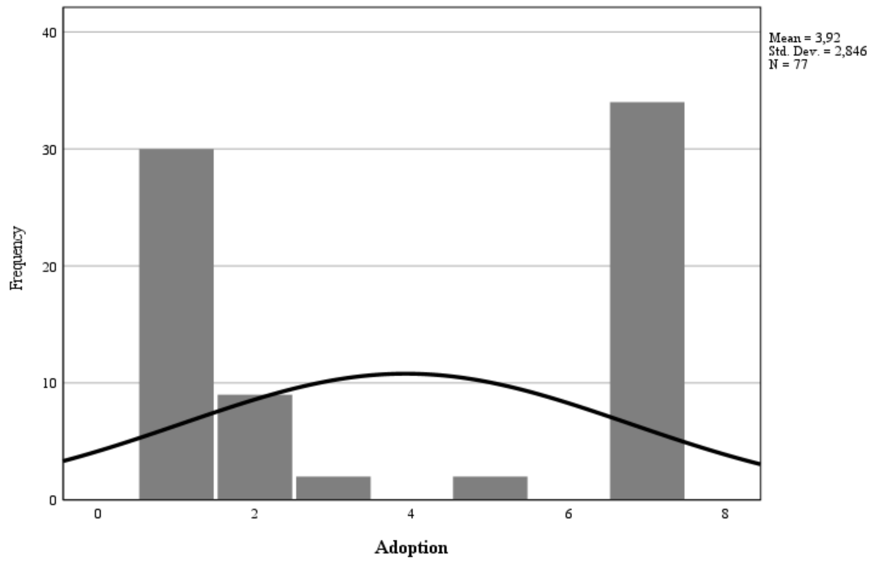

Figure 6: Distribution of dependent variable "adoption"(1=non adoption, 7=fully adoption) (SPSS output)

Following P. J.-H. Hu et al. (2002, p. 207), “adoption” was therefore recoded into a dummy variable taking the values of 0 for non-adopters and 1 for adopters. The minimum requirement for organizations to be considered adopters was the submission of a formal adoption proposal under review by the funding agency, thus including organizations that had already located and secured the funding and technology supply needed for technology adoption (values from 5 to 7 were recoded); however, non-adopting organizations not yet reaching the described threshold were recoded into non-adopters (values from 1 to 4 were recoded). Formal proposal submission, as suggested by P. J.-H. Hu et al. (2002, p. 207), serves as a threshold since a proposal under review is believed to eventually succeed, meaning that these organizations are therefore very close to technology acquisition. Moreover, since proposal submission is documented and observable, by submitting a formal proposal, an organization states a strong intention for and commitment to telemedicine. Using a dichotomous variable as the dependent variable, the conducted analysis was therefore a logistic regression. Logistic regressions are used to obtain the odds ratio in the presence of more than one independent variable (Sperandei, 2014, p. 13). While working similar to linear regressions, logistic regressions have a binomial response variable, resulting in the impact of each variable on the odds ratio of the dependent variable (Sperandei, 2014, p. 13). This entails modifying the structural model in Eq. 2 as follows:

(Eq. 3)

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 PEOU + \beta_2 PSB + \beta_3 PSR + \beta_4 PSN + \beta_5 CAM + \beta_6 PTS + \varepsilon,$$

where π indicates the probability of the outcome “adoption,” and β_1 to β_6 are the regression coefficients associated with the explanatory variables expressed as the factor loadings. β_0

represents the reference group, encompassing those individuals presenting the reference level of each independent variable.

6.5 Data analysis

6.5.1 Preliminary testing

Before engaging in analysis, the basic assumption for logistic regressions had to be met. They include independence of errors, linearity in the logit for continuous variables, absence of multicollinearity, and lack of strongly influential outliers. An adequate number of events per independent variable is also required to avoid an overfit model—a commonly recommended minimum "rules of thumb" being 10 to 20 events per independent variable (Stoltzfus, 2011, p. 1101). Table 10 summarizes the results for the different tested assumptions for logistic regressions:

Test	Statistic	Value		Conclusion
Autocorrelation	Durbin-Watson coefficient	1.933		No
Linear relationship	Box-Tidwell test	Interaction PEOU_	Sig. .101	Yes
		Interaction PSB_	Sig. .151	
		Interaction PSR_	Sig. .607	
		Interaction PSN	Sig. .656	
		Interaction CAM	Sig. .257	
		Interaction PTS	Sig. .503	
Multicollinearity	VIF	PEOU_	1.823	No
		PSB_	1.737	
		PSR_	5.047	
		PSN_	4.275	
		CAM	5.957	
		PTS_	1.262	
Outliers	Cook's distance	< 1		No
	Leverage	< twice or three times average leverage		No
	dfbeta	< 1		No
Number of events	EPV	6		Debatable

Table 10: Summary of performed tests for logistic regressions assumptions (own representation)

The independence of errors first assumes that all sample group outcomes are separate from each other (Stoltzfus, 2011, p. 1101). To test the independence of errors, Durbin–Watson (DW) statistics was used. This coefficient indicates whether the errors associated with one observation are not correlated with the errors of any other observation (Schreiber-Gregory & Bader, 2018, p. 15). The null hypothesis is that there is no autocorrelation; with a DW value between 1.5 and 2.5, the absence of first-order autocorrelation is confirmed, while DW values of less than 1.5 or greater than 2.5 indicate positive, respectively, negative autocorrelation (Schreiber-Gregory & Bader, 2018, p. 16). With a DW coefficient of 1.933, the absence of autocorrelation was confirmed. The second assumption for linear relationships for logistic regression requires the relationship between independent variables and their log odds to be linear (Schreiber-Gregory & Bader, 2018, p. 1). Different ways can be implemented to check this assumption, a typical method being to create a statistical term representing the interaction between each continuous independent variable and its natural logarithm (Stoltzfus, 2011, p. 1101), also known as the Box–Tidwell test. If the interaction is significant, the linearity assumption is violated (Tabachnik & Fidell, 2007, and Hosmer & Lemeshow, 2000, cit. in Stoltzfus, 2011, 1101). After running a Box–Tidwell test, none of the interaction terms were significant, thereby indicating the presence of a linear relationship between independent variables and their log odds. The third assumption is the absence of multicollinearity among independent variables: highly correlated independent variables will induce large standard errors for the estimated coefficients (Tabachnik & Fidell, 2007, and Hosmer & Lemeshow, 2000, cit. in Stoltzfus, 2011, p. 1101). Similar to the multicollinearity test conducted in Chapter 5.4.1, VIF was inspected, with VIFs exceeding 10, indicating serious multicollinearity requiring correction (Schreiber-Gregory & Bader, 2018, p. 3). All the variables resulted in VIF values below 10, therefore showing no indication of multicollinearity. Finally, logistic regressions require the absence of strongly influential outliers, meaning that a sample member's predicted outcome should differ from the actual outcome, as too many such outliers might compromise the model's overall accuracy (Stoltzfus, 2011, p. 1101). Outliers were detected using Cook's distance: this first measure allows to identify and isolate those points that excessively influence the model, with cutoff values exceeding 1 showing a strong influence of the outlier on the model (Cook & Weisberg, 1982, cit. in Field, 2009, p. 217). A second measure used was leverage, which indicates the influence of the observed value of the outcome variable over the predicted values; leverage values can lie between 0 (no influence) and 1 (complete influence) (Field, 2009, p. 217). With no influence over the model, all expected leverage values should be close to the average leverage value, defined as $\frac{(k+1)}{n}$, k being the number of predictors in the model, and n

the size of the sample (Field, 2009, p. 217), therefore $\frac{(k+1)}{n} = \frac{(6+1)}{77} = .09$. The literature recommends paying particular attention to cases with values exceeding twice (Hoaglin and Welsch, 1978, cit. in Field, 2009, p. 217) or three times (Stevens, 2002, cit. in Field, 2009, p. 217) the average leverage. Lastly, dfbeta is also a common measure of influence in that it states the difference between a parameter estimated using all cases and estimated when one case is excluded. Considering the values of dfbeta, it is possible to identify cases that largely influence the parameters of the regression model (Field, 2009, p. 218). Absolute values above 1 indicate cases that substantially influence model parameters (Field, 2009, p. 219). The results for the tested measures Cook's distance and leverage are shown in Appendix 5 and for dfbeta in Appendix 6. None of the measures showed the presence of an outlier dramatically influencing the model. Values for Cook's distance ranged well below one, whereas most of the leverage values were located below the recommended cutoff value by Hoaglin and Welsch (1978, cit. in Field, 2009, p. 217) of twice the average leverage, with higher values still below three times the average, as recommended by Stevens (2002, cit. in Field, 2009, p. 217). Also, dfbeta values ranked below 1, indicating no strongly influential outliers. Lastly, the adequate number of outcomes per independent variable was checked since a correct number of outcomes allows us to avoid an overfit model and therefore model instability (Stoltzfus, 2011, p. 1101). The literature suggests a rule of thumb of 10 to 20 outcomes (also called events) for each binary category (Stoltzfus, 2011, p. 1101), meaning that one explanatory variable can be studied for every 10 or, more conservatively, 20 outcomes. A key concept here is the number of events per variable (EPV), which is calculated as the ratio between the number of events and the number of predictors, the number of events being the smaller of the number of subjects experiencing the outcome and the number of subjects without the outcome experience (Austin & Steyerberg, 2017, p. 797). Table 11 shows that the smallest observed number of subjects exposed to the outcome was 36 (adoption = 1), which induces an EPV of $\frac{36}{6} = 6$, therefore falling below the recommended value of 10. This might be caused by the small sample size, as suggested by Van Smeden et al. (2016, p. 11), who, nonetheless, also identified the EPV = 10 rule as a minimal sample size criterion for binary logistic regression analysis as weak, which leaves this particular indicator unclear.

	Observed		Predicted		
			Adoption		Percentage Correct
			0	1	
Step 1	Adoption	0	30	11	73,2
		1	16	20	55,6
	Overall Percentage				64,9

a. The cut value is ,500

Table 11: Classification table for number of events (SPSS output)

6.5.2 Results

To perform the logistic regression analysis, the default method was used, which places all the predictors into the regression model in one block, and parameter estimates are calculated for each block (Field, 2009, p. 271). This method was preferred over the other existing stepwise methods, which either add or remove predictors based on how the model fits the data (Field, 2009, p. 272) since all predictors rely on previous theoretical research (Field, 2009, p. 212) and are not influenced by random variation in the data (Stundenmund & Cassidy, 1987, cit. in Field, 2009, p. 212). First, significance and accuracy of the model were tested. The omnibus test of model coefficient shown in Table 12 tests the null hypothesis that the full model does not represent a significant improvement compared to the null model. The results show that the research model showed a significant improvement from the baseline model, as suggested by the goodness-of-fit statistic having a chi-square of 11.783 and a level of significance of .90.

		Chi-square	df	Sig.
Step 1	Step	11,783	6	,067
	Block	11,783	6	,067
	Model	11,783	6	,067

Table 12: Omnibus test of Model Coefficients (SPSS output)

However, the Hosmer–Lemeshow goodness-of-fit test tests the null hypothesis that the model is a good enough fit for the data. A significance value less than .05 indicates a poor fit; as shown in Table 13, with a p-value slightly over.05, the null hypothesis could be rejected, however, without indication of a solid fit. Nonetheless, since the power of statistical tests increases with sample size (Nattino et al., 2020, p. 550), the poor fit found in Table 13 might again be related to the small sample size.

Step	Chi-square	df	Sig.
1	15,113	8	,057

Table 13: Hosmer and Lemeshow Test (SPSS output)

Finally, Table 14 overviews how well the model predicts group memberships or, alternatively, how many of the predicted adopters and non-adopters were correctly classified. Based on the discussed adoption threshold, the data included 36 adopting and 41 non-adopting organizations. This would result, in theory, in a classification accuracy of 50.20%, that is, $\left(\frac{36}{77}\right)^2 + \left(\frac{41}{77}\right)^2 = 0.502$. As shown in the results, the model predicted that there were 46 organizations that did not adopt telemedicine and 31 that did adopt the technology; in the end, 30 non-adopting organizations out of 41 observed ones were correctly classified and so were 20 adopting organizations out of 36, accounting for a correct classification of 73.2% and 55.6%, respectively, and an overall classification accuracy achieved by the research model of 64.90%, which considerably exceeds that of random chance, thereby suggesting the reasonable discriminant power of the model.

		Predicted		
		Adoption		Percentage
	Observed	0	1	Correct
Step 1	Adoption 0	30	11	73,2
	1	16	20	55,6
	Overall Percentage			64,9

a. The cut value is .500

Table 14: Classification Table (SPSS output)

Support for the structural hypotheses was evaluated by examining the respective odds ratio, the associated statistical significance, and the confidence interval. When examining the output of logistic regressions, the value of the odd ratio is crucial to the interpretation. Odds ratio is an indicator of the change in odds resulting from a unit change in the predictor and is defined as the probability of an event occurring divided by the probability of that event not occurring; therefore, if the odd ratio value exceeds 1, it indicates that with a one-unit increase in the predictor, the odds of the outcome occurring increase and, conversely, an odd ratio value below 1 indicates that with a one-unit increase in the predictor, the odds of the outcome occurring decrease (Field, 2009, pp. 270–271). As summarized in Table 15, only PEOU and PSB appeared to be significant, with p-values of .045 and .063, respectively. Considering the model, PSB, PSN, and PTS all showed values above 1, which indicates increasing odds of the outcome occurring with a one-unit increase in the predictor. Both PSN and PTS were nonsignificant; furthermore, the direction and magnitude of the effect was not particularly surprising, as it showed that an increase in one unit in perceived service safety and, respectively, service needs would result in higher odds for an organization to adopt telemedicine, *ceteris paribus*. Although not significant, these findings nevertheless support the direction of the relationship postulated in Hypotheses 20 and 24. When interpreting for the significant predictor PSB, with a one-unit increase in PSB, the odds that an organization would adopt telemedicine were 1.470 times higher, *ceteris paribus*. Since odds are defined by the probability of an event occurring divided by the probability of that event not occurring, this can be translated into a probability of $p = \frac{ODDS}{(1+ODDS)}$ = 0.595 = 59.5%. Therefore, the probability that an organization would adopt telemedicine increased by almost 60% with an increase in PSB. These findings support Hypothesis 21, which postulated a significant and positive effect of PSB on telemedicine adoption. However, since the lower limit of the confidence interval fell slightly below 1 for all variables, there is a slim possibility that in the population the direction of the relationship is the opposite (e.g., negative) as what was observed, cautioning the interpretation. PEOU, PSR, and CAM reported odds ratios below 1, which indicates decreasing odds of the outcome occurring with a one-unit increase in the predictor. As outlined earlier, only PEOU was significant and yielded the odds of an organization to adopt telemedicine to decrease by .508 with a one-unit increase in the predictor, *ceteris paribus*. The probability that an organization would adopt telemedicine hence decreased by 33.70% with an increase of PEOU. These findings corroborate Hypothesis 19, which postulated a significant and negative effect of PEOU on telemedicine adoption. Both limits of the confidence interval of PEOU fell below 1, which indicates the trueness of the observed direction in the population. Both PSR and CAM were nonsignificant. For variable PSR, with a one-unit increase in PSR, the odds that an organization would adopt telemedicine would decrease, *ceteris paribus*, supporting the postulated direction in Hypothesis 22. However, Hypotheses 23 was rejected, as the results showed a nonsignificant and negative effect of CAM on adoption other than the significant and positive relationship postulated. These last results, despite being nonsignificant, came as surprising: as the findings suggest, with a stronger collective attitude, the less likely an organization was in an advanced adoption phase and therefore less likely to use telemedicine. Nevertheless, the large confidence interval for CAM only allows speculation about the direction of the association. These findings are only partially similar to the results of P. J.-H. Hu et al. (2002), as correspondence was only found for the effect of the variable PEOU, which was observed to significantly negatively affect telemedicine adoption. The results for PSR are similar to the findings of P. J.-H. Hu et al. (2002) in the direction, although not significant. Other than the findings by the authors, the effect of PSB was found to be significant and positive, as also postulated by P. J.-H. Hu et al. (2002) but not supported by their findings; vice versa, the effect of CAM on telemedicine adoption was not supported in the present paper and with a direction contrary to what was postulated.

Table 15: Binary logistic regression results (SPSS output)

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	PEOU_loadings	−.677	.338	4.019	1	.045	.508	.262	.985
	PSB_loadings	386	.207	3.456	1	.063	1.470	.979	2.208
	PSR_loadings	−.466	.452	1.062	1	.303	.627	.259	1.523
	PSN_loadings	.291	.547	.283	1	.595	1.338	.458	3.910
	CAM_loadings	−.604	.411	2.153	1	.142	.547	.244	1.225
	PTS_loadings	.383	337	1.293	1	.255	1.467	.758	2.841
	Constant	.924	1.644	.316	1	.574	2.520		

a. Variable(s) entered on step 1: PEOU_loadings, PSB_loadings, PSR_loadings, PSN_loadings, CAM_loadings, PTS_loadings.

7. DISCUSSION

Amid the COVID-19 pandemic, the utilization of telemedicine has been observed to increase to provide care for patients at home with mild COVID-19 or COVID-19 symptoms and to medically manage non-COVID-19-related issues (Tsikala Vafea et al., 2020, p. 254). As a matter of fact, almost half of the respondents to the administered questionnaire declared that they had made more use of telemedicine during the pandemic, suggesting that COVID-19 had some influence on the increased use of the technology. These findings, however, do not yield any information about which factors were crucial to adoption or non-adoption decisions. Motives for adoption decisions of telemedicine were therefore analyzed building on P. J.-H. Hu et al. (2002) explorative study in Hong Kong healthcare organizations and by means of CFA and path analysis.

When first analyzing the measurement model through CFA, despite evidence showing a good fit of the hypothesized six-factor CFA model with the sample data, some observed variables did not quite show high correlations with their respective factors as expected, namely PEOU1, PTS1, PTS2, PSB1, and PSR1 or, in other cases, displayed an appreciably higher association than expected, as for PSB5 and PSR2, respectively, presented parameters' values that were substantially lower than postulated, such as for CAM3. These deviations from the formulated hypotheses are discussed briefly below. PEOU1, which corresponds to the observed variable "ease to become skillful" with telemedicine, is associated with the notion of learnability (Davis, 1989, p. 325). Since telemedicine requires some digital skills to be operated on, some authors argue that an informatics skills gap might be conducive to problems in the operation of telemedicine itself (i.a., Pathipati et al., 2016; Kuhn & Jungmann, 2018; Sapci & Sapci, 2019). This digital literacy gap due to the demographics of Swiss doctors, as postulated by Nittas and Von Wyl (2020, p. 2), or related to the type of formal training received, as suggested by Kuhn and Jungmann (2018, p. 256), could explain the moderate association between the observed variable ease in becoming skillful and the factor PEOU. PTS1 entailed the necessity of governmental certification for telemedicine to be perceived as safe. In the Swiss context, the legal basis for the implementation of digitalization—and telemedicine—in outpatient healthcare varies greatly from canton to canton, and in many cantons, the legal framework does not keep up with the current situation (Zingg et al., 2019, p. 115). This heterogeneity in the legal framework might therefore be a cause for the moderate association between governmental certification of telemedicine to be perceived as safe and perceived technological safety. Similarly, for PTS2, which equaled the necessity of certification of medical professional societies to be perceived as safe, there is reason to believe that although telemedicine is in principle accepted by the largest medical professional society in Switzerland (the so-called FMH), there are still several open questions cited by the FMH itself that may hold professionals back from using this technology (Zingg et al., 2019, p. 114). As for the variable PSB1, depicting a better timeliness of patient care when using telemedicine, the literature finds it to be particularly important when intervening in rural or remote areas (Mohr et al., 2018, p. 590). Since the respondents worked mainly in cantonal or university hospitals, these facilities cannot be said to be purely rural but are mostly located in densely populated areas such as cities, having a proximity of means that do not necessarily include telemedicine, which therefore might not be perceived as particularly beneficial regarding the timeliness of patient care. Moreover, Switzerland benefits from a very high hospital density by international standards; 99.8% of the population can reach a general hospital by car within 30 minutes, and three-quarters of the population can choose from eight different hospitals (Cosandey, 2020, n.p.). Interestingly, the variable PSR1, representing the perceived risk that telemedicine might hinder the physician–patient relationship, was also found to be moderately associated with the factor perceived risk. This might partly be due to the pandemic situation, where restrictive measures require both providers and patients to balance giving or receiving care and minimizing risk, therefore forcing re-evaluating the patient–doctor relationship (Nittas & Von Wyl, 2020). Furthermore, the recent technological advances in medicine have changed the role of patients, who have evolved active, well-informed, and responsible participants in the healthcare system that seek advice on their own and refer to their practitioner to obtain reliable information (Brockes et al., 2017, p. 899). Telemedicine in itself would therefore not represent the reason for the different doctor–patient relationship but rather the current patients’ self-determination. Improved overall effectiveness of patient care, such as captured by PSB5 and its counterpart PSR2 reducing patient care effectiveness, showed a higher association than expected with the respective factors PSB and PSR, meaning that those who believed that telemedicine improved patient care effectiveness strongly associated it with a benefit from the technology, and those who considered telemedicine to reduce patient care effectiveness strongly associated it with a risk of the technology. These results are not particularly surprising since the notion of effectiveness in the healthcare sector implies that the effect of medical intervention should change the natural history of a particular disease for the better (Cochrane, 1972, cit. in Burches & Burches, 2020, p. 2). To be considered effective, telemedicine must therefore prove to enhance healthcare outcomes through its services (Zhai et al., 2014, p. 1)—if this happens, the technology is credited with bringing benefit, if not, with carrying risk. Finally, the observed variable CAM3, accounting for the attitude toward increased use of IT in patient care, showed a substantially lower correlation with the CAM factor than expected, meaning that the increased use of IT in patient care would not depict CAM very well. As it is now ascertained that the healthcare sector has lagged behind many other industries in harnessing the digital momentum (OECD, 2019, p. 17), the literature traces this delay to firm structural, organizational, and institutional barriers that are embedded in healthcare systems (OECD, 2019, p. 32), hence, not directly related to the attitudes of professionals, which is much more influenced by direct interventions into their day-to-day activities (i.a., Anderson, 1997, and Anderson & Aydin, 1997, cit. in Chau & Hu, 2002, p. 298; Rho et al., 2014, p. 560).

The greatest implications are deduced from the second part of the analysis, that is, the examination of the significant variables in the structural model. Similar to P. J.-H. Hu et al. (2002), PEOU showed a negative and significant effect on telemedicine adoption, suggesting that the more advanced an organization was in adoption, the less PEOU played a role in it. PEOU, as defined by the literature, expresses the degree to which a person believes that using a particular technology is free of effort (Lin, 2013, p. 244). As argued by Hackbarth et al. (2003, p. 221), this perception is closely linked to experience: users normally perceive a system as easier to use as they earn more knowledge and confidence through direct experience in employing the system, with direct experience being identified as the most influential mechanism raising an individual's confidence in achieving effective performance levels. It is therefore fair to assume that the more into adoption, the greater the exposure time of the organization and users to the technology, and thus their experience, leading users to perceive the task and the technology as easier than when they first started (Kanfer & Ackermann, 1989, and Kanfer et al., 1994, cit. in Hackbarth et al., 2003, p. 222). However, increased experience improving PEOU does not provide any information about the users' perceptions toward the technology itself (Hackbarth et al., 2003, p. 222) nor their intention to use it (Bhattacherjee & Hikmet, 2007, p. 734). As noted by Venkatesh (2000, p. 360), individual's general beliefs on technology and technology use represent the strongest determinants of technology-related ease of use. That is, at all stages of user experience with a specific technology, system-independent motives, such as users' attitudes toward technology, play a stronger role than adjustments resulting from the user-system interaction (Venkatesh, 2000, pp. 355–356). This argument is supported by Kuo et al.'s (2015, p. 391) study on the influence of experience on the adoption of telemedicine, where more favorable physicians toward telemedicine are likelier to use the technology in their practice; for experienced physicians, this effect was found to be stronger than in inexperienced physicians since they find the technology easier to use. These conclusions have important practical implications, as they place greater emphasis on system-independent constructs that go beyond the user–system interaction. Attempts at designing systems that are easy to use should therefore place greater focus on individual difference variables and encourage experienced physicians to share their facilitative telemedicine experiences with inexperienced physicians to foster more positive attitudes toward telemedicine technology usage and therefore boost telemedicine adoption within their organization, as suggested by Kuo et al. (2015, p. 391). Considerations on PSB also are essential. The results of the logistic regression showed a positive and significant effect of PSB on adoption, the effect being translated into a strong 59.50% higher probability of an organization adopting telemedicine with an increase in the perceived benefits of the technology. These results opposed those of P. J.-H. Hu et al. (2002), who found the effect of PSB to be nonsignificant. The authors attributed the reasons to the lack of knowledge about telemedicine at the time and whose potential adoption or intention to adopt being mostly driven by considerations differing from specific service benefits, such as clinical feasibility, technology exploration, and professional status enhancement (P. J.-H. Hu et al., 2002, p. 215). Two decades and a global pandemic later, these considerations might no longer hold up. As defined by the literature, successful adoption of telemedicine in routine practice takes place when it is perceived as a benefit to medical or health-related issues (Obstfelder et al., 2007, n.p.). With the COVID-19 pandemic and physical proximity being replaced by distancing and limited access to certain types of care (Nittas & Von Wyl, 2020, p. 1), telemedicine has been widely utilized to provide care for patients at home (Tsikala Vafea et al., 2020, p. 254) and is currently indicated as the industry standard (KPMG, 2020, p. 16): following the better knowledge and diffused use of telemedicine, physicians' concerns on incorporating telemedicine into their practice might considerably outweigh the perceived risks. These considerations probably explain the non-significance of the counterpart PSR, which at the time was instead found to be a significant variable in the study by P. J.-H. Hu et al. (2002).

7.1 Limitations and further research

These analysis results are subject to certain limitations. From the theoretical viewpoint, despite having established itself as an appropriate approach for investigations of organizational technology adoption, the majority of the theoretical development related to the TOE framework has been limited to enumerating the different factors relevant in various adoption contexts (Baker, 2012, p. 237). Alternatively, no other or new constructs have been added to the framework, which probably indicates little development of this approach. Nonetheless, the freedom provided by the TOE framework allowing variation in the factors or measures for each new research context makes this approach highly adaptable, which in turn might explain why scholars have seen little need to adjust or refine the theory itself (Straub, 2009, p. 237). From a methodological viewpoint, some limits are set by the voluntary participation in the questionnaire, which makes responses more prone to self-selection biases or, alternatively, only physicians who were interested in telemedicine might have been likelier to fill in the questionnaire. Moreover, the present study does not discriminate by medical specialty, an aspect emphasized by the respondents, who sometimes reported that they could not identify with any stage of adoption simply because telemedicine is not applicable in their discipline. Given the small sample, a detailed analysis by medical discipline would not have yielded representative results; however, this aspect should be considered for future studies. One major constraint, however, is represented by the chosen method of the two-step FSPA. The literature has shown that employing factor scores in a linear regression results in biased estimates of the regression parameters (Devlieger & Rosseel, 2017, p. 31). Factor scores are not solely determined by the measurement models, and this uncertainty cannot be ignored (Kelcey, 2019, p. 84). Several methods have been developed to address this issue. Among them, the Croon's method (2002) thoroughly corrects this bias (Devlieger & Rosseel, 2017, p. 31). As illustrated by Devlieger and Rossell (2017, pp. 31–32), this method lies on the assumption that there is a difference between the variances and covariances of the factor scores and the variances and covariances of the true latent variable scores. Hence, Croon (2002) used estimates of the variances and covariances of the true latent variable scores instead of the factor scores. This so-called bias-corrected factor score analysis (BCFSCA) would therefore be more appropriate in providing more fitting results and better handling small samples or more complex models, such as in this case (Devlieger & Rosseel, 2017, p. 36). However, choices not to employ this method were also determined by the relative dearth of empirical studies employing BCFSCA (Kelcey, 2019, p. 84), recent reviews suggesting that the underuse of the method may be due to unfamiliarity of the method to the applied researchers, lack of practical and accessible guidance and software availability, and absence of comparisons against full information methods grounded in discipline-specific examples (Lu et al., 2011, cit. in Kelcey, 2019, p. 84).

8. CONCLUSIVE REMARKS

Digitalization has enabled enormous progress in all sectors of society and economy recently. In the healthcare sector, despite having the potential to bring numerous advances regarding both technical medical innovation and public health, digitalization is still struggling to make inroads. Among the different eHealth initiatives encouraging the implementation of various ICT services or systems in healthcare, telemedicine is probably the one with the longest history, discussions, and solutions on the remote interaction between patients and doctors, retracing the 1980s. In Switzerland, the topic of telemedicine has been around since the early 2000s, speaking for a rather mature telemedical ecosystem. However, despite the apparent benefits claimed by telemedicine advocates, telemedicine utilization among Swiss healthcare actors has remained stagnant. Today, with the COVID-19 pandemic and physical proximity being impossible or limited, a reverse trend has been observed, with telemedicine being widely utilized to provide care for patients at home with mild COVID-19 or COVID-19 symptoms and to medically manage non-COVID-19-related issues. Nonetheless, despite recent evidence suggesting a reorientation of the medical personnel favoring telemedicine, the literature does not tackle the issue of the disposition of Swiss physicians to fully adopt telemedical services in the post COVID-19 era. The present study precisely aimed to identify the factors determining organizational technology adoption decisions to properly picture Swiss physicians' disposition to adopt telemedicine outside the crisis. To do so, a two-step analysis was conducted. First, a CFA based on the findings of P. J.-H. Hu et al. (2002) and complemented by prior empirical evidence was performed. A hypothetical model specifying the relations between the six latent variables PSB, PSR, PSN, CAM, PEOU, and PTS and their respective observed variables was tested to assess how well the observed variables represent the number of constructs. The data were collected by administering an online questionnaire to Swiss physicians in Swiss cantonal and university hospitals. The goodness-of-fit statistics found for CFA suggested a good fit of the hypothesized six-factor CFA model with the sample data. All factor loadings were statistically significant and showed appreciable high and positive levels of association between the observed variables and their respective factors, therefore confirming the postulated structure of the model as tackled by the first research question, "*Do the hypothesized six factor structures by P. J.-H. Hu et al. (2002) adequately fit with the sample data?*". In the second step, the effect of the six factors previously confirmed using a CFA on organizational adoption decisions was analyzed using a two-step FSPA. This second stage of the analysis allowed us to answer the second research question of the paper, "*How do the six factors PSB, PSR, PSN, CAM, PEOU, and PTS predict the adoption of telemedicine technology in Swiss healthcare organizations* *during the COVID-19 pandemic?"*. The effects of the variables PSR, PSN, CAM, and PTS were nonsignificant, with CAM showing a surprising negative result on adoption, suggesting that the stronger the collective attitude, the less likely an organization was in an advanced adoption phase and therefore to use telemedicine; however, since the results for these variables are nonsignificant, they cannot be confidently interpreted. This might represent a line of future inquiry in that the BCFSCA approach should be applied to probably bear more accurate results. The results for the two remaining significant variables only partially confirmed the findings by P. J.-H. Hu et al. (2002), in that PEOU significantly negatively affected telemedicine adoption, suggesting that the more advanced an organization was in adoption, the less PEOU played a role in it. Linking PEOU to experience, as suggested by the literature, these findings bear some important practical implications, in that they place greater value on individual beliefs on technology and technology use, rather than user–system interaction. That is, when introducing a new technology that is easy to use into an organization, special attention should be given to individual difference variables, encouraging experienced physicians to share their experiences of telemedicine with inexperienced physicians to foster more positive attitudes toward telemedicine technology usage and therefore boost telemedicine adoption within their organization. The effect of PSB was also significant and positive in the direction, which indicated that the higher the probability of an organization adopting telemedicine, the higher the perceived benefits of the technology. These findings reveal a better recognition of telemedicine following digital progress and the acknowledged benefits of telemedicine following the COVID-19 pandemic. Overall, PEOU and PSB are likely better and more significant predictors of organizational telemedicine adoption in Swiss healthcare organizations regarding the COVID-19 pandemic.

Appendix

Appendix 1: Questionnaire

1. **Welcome page and understanding statement**

   Dear participant,

   welcome and thank you very much for participating in the study I am conducting for my master thesis at the University of Bern in "Public Management and Policy".

   The goal of the following study is to gather deeper insights into the adoption of telemedicine in Swiss healthcare organizations during the COVID-19 pandemic.

   The questionnaire will take about 10 - 12 minutes to complete. Your participation is voluntary. You can cancel or revoke your participation in the study at any time. Data will be collected anonymously and are strictly confidential. Data will only be evaluated for scientific research purposes by the University of Bern.

   If you know of anyone else interested in participating in the survey within your organization, please feel free to share the link. The link is active until Sunday, February 21, 2021.

   By clicking on the "continue" button you agree that your data will be used exclusively for this study.

   Thank you very much for your participation!

2. **Adoption phase**

   Q1: Please assess to what extent telemedicine* is currently in use within your organizational unit:

Already adopted telemedicine technology and used it for clinical purposes.
Have located and secured financial resources and technology source.
Have put together a formal proposal that is currently under external review.
Have or are about to complete an adoption plan to be submitted to a funding agency.
Have designated a task force or individuals to investigate potential adoption.
Informally discussed potential adoption but have taken no concrete actions.
Thought about potential adoption but decided not to pursue at present time.
None of the above options apply to me, please specify why:

Questions directly related to telemedicine follow. Please answer by keeping the *current pandemic context* in mind.

3. Technological context

Q2: Below you will find some statements that describe telemedicine as being better than or superior to existing service arrangements. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don't know
Telemedicine improves the timeliness (rapidity) of patient care.								
Telemedicine reduces costs of patient care and service.								
Telemedicine improves service productivity of medical staff.								
Telemedicine reduces unnecessary patient transfers or admissions.								
Telemedicine improves overall effectiveness of patient care.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

Q3: Next, you will find some statements that summarize telemedicine's claimed risks. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don't know
Telemedicine hinders physician-patient relationship.								
Telemedicine reduces patient care effectiveness								
Telemedicine jeopardizes patient privacy.								
Telemedicine brings psychological harm.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

Q4: The next question concerns the concrete handling of telemedicine. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don't know

It is easy to become skillful in using telemedicine.								
Telemedicine is flexible to interact with.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

Q5: The next question is about safety considerations. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don't know
Telemedicine must be certified by a competent government authority to be considered safe.								
Telemedicine must be endorsed by medical professional societies to be considered safe.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

4. **Organizational context**

Q6: The following question is about how you relate to telemedicine. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don't know
I support telemedicine-empowered virtual patient care.								
I support telemedicine assisted consultation.								
I support increased use of IT in patient care.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

5. **Environmental context**

Q7: The next question deals with the service provided by telemedicine to the external world. Please rate how much you agree with these statements on a scale from 1 (=strongly agree) to 7 (=strongly disagree).

	1 = strongly agree						7 = strongly disagree	I don’t know
Telemedicine addresses unmet patient service needs.								
Telemedicine closes an existing service gap.								

Definition: the term telemedicine refers to the whole practice of medical care delivery, from receiving a consultation from a health professional online or via app, where conversations and diagnoses can be undertaken, for example, by telephone, video, or with the help of pictures, to the actual treatment, health education and transfer of medical data.

6. Respondent profile

In conclusion, a couple of questions about your person and your professional path follow.

Q8: Gender

Male
Female
non-binary / third gender
I prefer not to say

Q9: Age

Q10: Please state at which institution you attended medical school (please refer to the institution where you obtained your Master's degree).
If you did not attend medical school, please indicate where you obtained your highest degree.

Q11: Please state at which organization(s) you completed your residency (multiple answers possible). If you have not completed a residency, please answer the question with "-".

Q12: Hierarchical position held at the organization in which you currently work.

Hospital executive officer
Medical director
Assistant medical director
Chief physician (Chefarzt*/Médecin chef/Primari*)
Lead physician (Leitende* Arzt*/Médecin dirigeant*/Medico aggiunt*)
Head of Clinic (Oberarzt*/Chef* de clinique/Capoclinica)
Assistant doctor (Assistenzarzt*/Médecin assistant*/Medico assistente)
Other:

Q13. Please state your medical specialty.

I am not a doctor
allergology and clinical immunology
anesthesiology
angiology
cardiac and thoracic vascular surgery
cardiology
clinical pharmacology and toxicology
dermatology and venereology
endocrinology
gastroenterology
general and trauma surgery

gynecology and obstetrics
hand surgery
hematology
immunology
infectiology
intensive care
internal medicine
legal medicine
medical genetics
medical oncology
nephrology
neurology
neurosurgery
nuclear medicine
ophthalmology
oral and maxillofacial surgery
orthopedics and traumatology
otolaryngology
pathology
pediatric surgery
pediatrics
pharmaceutical medicine
physical and rehabilitative medicine
plastic, reconstructive, and aesthetic surgery
prevention and Public Health
primary care
psychiatry and psychotherapy
pulmonology
radiology
radio-oncology/radiotherapy
rheumatology
thoracic surgery
tropical medicine

urology
vascular surgery
work medicine

Q14: Please state the location of your healthcare organization (Canton).

AG
AI
AR
BE
BL
BS
FR
GE
GL
GR
JU
LU
NE
NW
OW
SG
SH
SO
SZ
TI
TG
UR
VD
VS
ZG
ZH

Q15: Please state the legal status of your healthcare organization.

Cantonal hospital
Private hospital
University hospital
Other:

7. Conclusion

You have almost reached the end of the questionnaire! A couple of questions follow to conclude.

Q16: During the COVID-19 pandemic, I made significantly more use of telemedicine.

Yes
No
I don’t know

Q17: I answered this questionnaire honestly and conscientiously.

1=fully						7=not at all	I don’t know

Q18: Do you have any comments?

Appendix 2: Normality tests CFA

Appendix 2: Normality tests CFA (SPSS output)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PSB1	.182	77	.000	.920	77	.000
PSB2	.159	77	.000	.931	77	.000
PSB3	.130	77	.003	.949	77	.004
PSB4	.220	77	.000	.893	77	.000
PSB5	.172	77	.000	.939	77	.001
PSR1	.182	77	.000	.906	77	.000
PSR2	.123	77	.006	.952	77	.005
PSR3	.198	77	.000	.908	77	.000
PSR4	.219	77	.000	.885	77	.000
PEOU1	.223	77	.000	.889	77	.000
PEU2	.216	77	.000	.904	77	.000
PTS1	.178	77	.000	.911	77	.000
PTS2	.236	77	.000	.843	77	.000
CAM1	.181	77	.000	.909	77	.000
CAM2	.192	77	.000	.889	77	.000
CAM3	.265	77	.000	.814	77	.000
SN1	.204	77	.000	.904	77	.000
SN2	.228	77	.000	.850	77	.000

a. Lilliefors Significance Correction

Appendix 3: Multicollinearity test CFA

Appendix 3: Multicollinearity test CFA (SPSS output)

	Collinearity Statistics	
Model	Tolerance	VIF
PSB1	.328	3.049
PSB2	.453	2.208
PSB3	.340	2.944
PSB4	.399	2.504
PB5	.283	3.528
PSR1	.460	2.173
PSR2	.306	3.273
PSR3	.375	2.669
PSR4	.359	2.786
PEOU1	.473	2.116
PEOU2	.369	2.707
PTS1	.561	1.782
PTS2	.555	1.801
CAM1	.153	6.520
CAM2	.158	6.326
CAM3	.435	2.300
SN1	.473	2.116
SN2	.411	2.434

Appendix 4: Unstandardized factor loadings

Appendix 4: Unstandardized parameter estimates and significance (AMOS output)

			Estimate	S.E.	C.R.	P	Label
PEOU2	<---	PEOU	1.064	.212	5.008	***	
PEOU1	<---	PEOU	1.000				
PSB5	<---	PSB	1.051	.137	7.664	***	
PSB4	<---	PSB	1.077	.155	6.965	***	
PSB3	<---	PSB	.994	.140	7.119	***	
PSB2	<---	PSB	.896	.151	5.926	***	
PSB1	<---	PSB	1.000				
PSR4	<---	PSR	.975	.170	5.721	***	
PSR3	<---	PSR	.958	.167	5.748	***	
PSR2	<---	PSR	.996	.155	6.438	***	
PSR1	<---	PSR	1.000				
PSN2	<---	PSN	1.234	.242	5.101	***	
PSN1	<---	PSN	1.000				
CAM3	<---	CAM	.693	.097	7.129	***	
CAM2	<---	CAM	.978	.068	14.398	***	
CAM1	<---	CAM	1.000				
PTS1	<---	PTS	1.443	.169	8.554	***	aaa
PTS2	<---	PTS	1.443	.169	8.554	***	aaa

Appendix 5: Case summary of performed tests for logistic regressions assumptions: Cook's distance and leverage values

Appendix 5: Case summary for Cook's distance and leverage values (SPSS output)

Case Number	Cook's d	Leverage
1	.05860	.08137
2	.15030	.04712
3	.01571	.07482
4	.26929	.21345
5	.21284	.09425
6	.15357	.06686
7	.02337	.14470
8	.02411	.03572
9	.02673	.09151
10	.15728	.09397
11	.05089	.03739
12	.01758	.06366
13	.34075	.08560
14	.31270	.10437
15	.26200	.23124
16	.04529	.07182
17	.03459	.14583
18	.26133	.14675
19	.02144	.03894
20	.05769	.10644
21	.03982	.03695
22	.14105	.07083
23	.00879	.04850
24	.04209	.08696
25	.27711	.14512
26	.07389	.12903
27	.03392	.05597
28	.02826	.07475
29	.12383	.09279
30	.05370	.06640
31	.21852	.19175
32	.10721	.10865
33	.26861	.11846
34	.03841	.05465
35	.01552	.04218
36	.12093	.14056
37	.05335	.03055

Appendix 5: Case summary for Cook's distance and leverage values (SPSS output) (cont.)

Case Number	Cook's d	Leverage
38	.07211	.12393
39	.03691	.03785
40	.01712	.02003
41	.10547	.08811
42	.04740	.06360
43	.06041	.06801
44	.22730	.08370
45	.05556	.04869
46	.01420	.05346
47	.18993	.18462
48	.11106	.07288
49	.09219	.06378
50	.08716	.05652
51	.03721	.06181
52	.02665	.06695
53	.06365	.17308
54	.02987	.06183
55	.23444	.09220
56	.17274	.16995
57	.08219	.12524
58	.05865	.05877
59	.02225	.12513
60	.09624	.06934
61	.07717	.08652
62	.30450	.21713
63	.04928	.08876
64	.03087	.09245
65	.07900	.15184
66	.00897	.09988
67	.06984	.06977
68	.01906	.09689
69	.09426	.03782
70	.02063	.11374
71	.01959	.04351
72	.16433	.12491
73	.16359	.08842
74	.01314	.06062
75	.05563	.05648
76	.12171	.06865
77	.01428	.06322
Total N	77	77

Appendix 6: Case summary of performed tests for logistic regressions assumptions: dfbeta

Appendix 6: Case summary for dfbeta values (SPSS output)

Case Number	DFBETA for constant	DFBETA for PEOU_loadings	DFBETA for PSB_loadings	DFBETA for PSR_loadings	DFBETA for PSN_loadings	DFBETA for CAM_loadings	DFBETA for PTS_loadings
1	−.32459	.02562	.01544	.02836	.05151	−.02629	.03042
2	.08691	.08967	−.01807	−.00502	−.02205	.00120	−.06219
3	.00091	−.02605	.01443	.00051	−.00706	.00114	−.00082
4	.04246	−.02550	.07662	−.11420	.01810	−.02386	−.08856
5	−.05879	.00711	−.05505	.02581	.06306	.01798	.05935
6	−.21945	.03172	−.02375	.03403	−.10424	.09524	.02320
7	−.00379	−.03361	−.00457	.02154	−.01451	.01926	.01579
8	.10485	−.00982	.01297	−.03861	−.02632	−.01912	.02583
9	.13562	−.01675	.01351	−.05103	.02831	−.05609	.03674
10	−.08466	.09263	−.01739	−.01105	.06552	−.09083	.08064
11	−.04577	.00458	−.02895	.05285	.01142	.02206	.02149
12	.01198	−.03909	.01384	−.01325	.02327	−.00807	.00590
13	.16908	−.00477	−.03882	−.00950	−.18138	.15585	−.00237
14	−.01952	.01153	−.09359	.18338	.05452	.10250	−.09325
15	.42585	−.00395	−.07073	−.01949	.05910	−.07060	.06787
16	.07081	−.00709	.01543	−.00108	−.03643	.00193	−.03291
17	.03597	.01004	.00965	−.03944	.04749	−.07507	.04770
18	.49527	.08662	−.04763	−.06446	−.05928	−.07265	−.01284
19	.11376	−.02252	.00838	−.03215	.01808	−.02639	−.00232
20	−.24587	−.03378	−.00822	.07145	.06165	.02103	.02064
21	−.24012	.01372	−.01409	.06036	.05191	.00700	.00764

Appendix 6: Case summary for dfbeta values (SPSS output) (cont.)

Case Number	DFBETA for constant	DFBETA for PEOU_loadings	DFBETA for PSB_loadings	DFBETA for PSR_loadings	DFBETA for PSN_loadings	DFBETA for CAM_loadings	DFBETA for PTS_loadings
22	−.46184	.09961	−.01719	.07197	.04996	−.00938	.01813
23	−.00004	−.01946	.00809	−.00598	.02156	−.01830	.01266
24	−.04404	.00887	.01443	−.01119	.07670	−.06378	−.00063
25	−.19840	.07592	−.03737	.07890	.24975	−.10897	.00133
26	.20886	−.06112	.01771	−.03706	.00193	.00515	−.05293
27	−.06782	.01225	.02236	−.03838	.03468	−.05330	.02959
28	−.06261	.00195	.01716	−.00601	.04840	−.04788	.02142
29	.53143	−.01462	−.01132	−.07054	−.13044	.01887	−.03395
30	−.18752	.00800	.03233	−.01275	.03301	−.02078	−.01205
31	−.19805	.01691	−.03971	.15815	.02932	.05271	−.09874
32	−.10843	.01790	.00157	.06915	−.03609	.03318	−.05631
33	-.46773	.08091	.01556	.05208	−.14525	.10142	−.03678
34	.01878	−.00499	−.00723	.03431	−.01454	.00764	−.00623
35	−.03106	−.00724	.01281	−.01876	.01869	−.03122	.02875
36	.11957	−.05746	.00505	.00010	.07315	.00010	−.06947
37	.18906	−.00406	−.01758	−.00041	−.02281	.02767	−.03567
38	−.06012	−.06308	.01772	.02450	.01914	.04057	−.05171
39	.22523	−.01129	.01370	−.06273	−.00934	−.03002	−.00113
40	.05348	−.01159	.01243	−.02118	.00759	−.01454	.00408
41	−.47566	.05228	−.00642	.08538	.03644	.00978	.02727
42	.06557	.00758	.01081	−.02703	−.08881	.01036	−.00271
43	.16672	−.01444	−.00508	−.01603	.04069	−.02674	−.03732

Appendix 6: Case summary for dfbeta values (SPSS output) (cont.)

Case Number	DFBETA for constant	DFBETA for PEOU_loadings	DFBETA for PSB_loadings	DFBETA for PSR_loadings	DFBETA for PSN_loadings	DFBETA for CAM_loadings	DFBETA for PTS_loadings
44	−.26354	−.00960	−.03676	.09209	.14278	.04629	−.00500
45	.06383	−.00163	.01258	−.02054	.06638	−.03818	−.02528
46	.00522	−.02216	.01745	−.01598	.00872	−.01782	.01693
47	.07968	−.05457	.04376	−.10226	−.10416	.03244	.06834
48	−.16354	.08373	−.01271	.02928	.07039	−.06569	.03123
49	−.04794	.01872	−.00737	.04431	−.11051	.07022	−.02388
50	−.23686	.03476	−.01328	.04011	.02194	.00382	.06073
51	.07307	−.04181	.00623	−.03354	.00076	−.00263	.03029
52	.16027	−.01425	.02076	−.04708	.00057	−.04078	−.00313
53	−.14333	−.01889	.04693	−.05556	.03800	−.04166	.03707
54	−.05296	−.03191	.01383	.01573	−.01695	.02081	.00251
55	.38121	.00857	−.02456	−.05491	−.21349	.10454	−.06628
56	.35065	.03273	.03748	−.12236	−.13458	−.03383	−.05362
57	−.20414	−.02767	.01185	.07498	.04253	.02845	−.04451
58	−.10006	.03327	−.02681	.03758	.04386	−.02945	.03549
59	.06669	.00735	.01320	−.03952	.02336	−.05979	.02416
60	−.16101	−.02776	−.00125	.07029	−.06577	.10267	−.03575
61	.45641	−.02653	.00311	−.08108	−.05168	−.02491	−.01592
62	−.14442	−.08468	.02444	−.04265	.13147	−.00430	.08041
63	.05785	−.02199	.00112	−.00803	−.08643	.03109	.01895
64	.18917	−.02100	.02631	−.05932	−.03322	−.02739	−.00486
65	.12668	−.08439	−.00783	.00678	.00399	.03804	−.00182
66	.03959	−.01632	−.00029	−.00088	−.01504	−.00010	.01354

Appendix 6: Case summary for dfbeta values (SPSS output) (cont.)

Case Number	DFBETA for constant	DFBETA for PEOU_loadings	DFBETA for PSB_loadings	DFBETA for PSR_loadings	DFBETA for PSN_loadings	DFBETA for CAM_loadings	DFBETA for PTS_loadings
67	−.26729	−.00680	−.00808	.04992	−.01574	.04553	.04023
68	.00256	−.02756	.00436	−.00350	.03020	−.01968	.03533
69	−.04283	.05756	−.03025	.01354	.00363	.01552	−.02607
70	.11306	−.01111	.00579	−.02741	−.04168	−.01298	.01908
71	.02306	−.01270	.00379	.00632	.01886	−.02071	.01100
72	.21741	.00787	.00557	−.07922	−.19940	.04903	.02343
73	−.13217	.03993	.03854	−.07092	.05688	−.05284	.02615
74	.05432	−.02600	.01286	−.01243	−.01145	−.00583	.00568
75	.29928	−.02616	−.01211	−.02881	.01052	−.01962	−.00796
76	−.30348	.02405	.00838	.06152	−.03541	.07665	−.07867
77	−.06974	−.02152	.00999	.00674	.04172	−.01768	.01187
Total N	77	77	77	77	77	77	77

Statement of authorship

Ich erkläre hiermit, dass ich diese Arbeit selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel benutzt habe. Alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche kenntlich gemacht. Mir ist bekannt, dass andernfalls der Senat gemäss dem Gesetz über die Universität zum Entzug des auf Grund dieser Arbeit verliehenen Titels berechtigt ist.

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