Exploring trust in emerging technologies: an integrative model

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Abstract

This paper explored factors that influence technology trust beliefs, with a focus on differences between emerging and existing technologies. It was the first piece of evidence to test the “Faith-Confidence” grouping of technology trust predictors and it included two studies, based on PLS-SEM technique. Study 1 examined a structural model that includes individual differences, institutional-based trust, concern about privacy, calculus-based trust, and social norms. Study 2 addressed limitations of Study 1 and assessed relationships between these variables and technology trusting beliefs. The studies also compared path estimate strength between technologies using multi-group analysis. The studies were controlled randomized post-test experiments with a total of 629 participants.

The studies found significant differences in how trust is developed for emerging versus non-emerging technologies and that "Faith" is a stronger predictor for trust in emerging technologies, while "Confidence" is stronger for existing technologies. The paper also introduced two new constructs - perceived power asymmetry and technological savviness - to the technology acceptance domain. Future research should replicate the study for various technologies and cultures and expand the proposed model on actual technology usage.

Keywords: trust in technology, emerging technologies, existing technologies, faith and confidence predictors of trust, PLS-SEM, MGA

Introduction

In the early twenty-first century, the train of progress is again pulling out of the station. Those who miss this train will never get a second chance

Y. N. Harari, Homo Deus: a Brief History of Tomorrow

The rapid pace of technological change in recent decades has made life more challenging for both producers and users of technology, and trust in technology has become a central focus of research. The importance of trust has been recognized in social and philosophical literature, with J.S. Mill's quote – "the advantage to mankind of being able to trust one another penetrates into every crevice and cranny of human life" (Furlong, 1996, p.2) – emphasizing the impact of trust on both micro- and macro-economic levels of society. This idea has been embraced since the end of the 19th century.

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Yet, despite the seeming obviousness of this idea, the conceptualization and prioritization of trust research has received an unjustified lack of consideration in the past, especially in the economic domain (Arai, 2007; Knack, 2001). Arai (2007) argues that, as the neoclassical economic schools prevailed in the world, the lack of attention to trust has caused massive disruption in markets, large corporations, and between individuals, resulting in social chaos and inefficient allocation of resources. Thus, trust poses a number of theoretical puzzles to the researchers, since relying on a complete stranger's word "violates rational-actor models" (Dunning et al., 2019). It seems that the last decades indeed have shown the necessity of cross-disciplinary research on trust, which recently has been gaining an ever-growing attention (Furlong, 1996).

Recent studies are demonstrating the key role of trust and trustworthiness for the economy. Smith (2020) found that a 10% increase in the share of trusting population in a country could, on average, result in a 0,5% growth of a real annual GDP per capita. Fehr (2009) showed that trust also increases efficacy of existing human and physical capital inputs. Apart from that, social trust was proven to have affected the rate of development of different comparable countries on multiple occasions (e.g., Beugelsdijk, 2004; Bjørnskov, 2012). Kalish et al. (2021) summarize the findings on positive influences of trust on the economic sector at all levels: reduction in transaction costs and stability in financial sector, allowed by trust formation, draw bigger quantities of business investment, while also contributing to human capital building, followed by organizational structure change and improved export sales. Consequently, these factors result in the increase of GDP per capita and the economic development pace.

Trust in technology, in particular, is a crucial part of social trust, since in the current reality digital ecosystems are becoming embedded in people's lives. The importance of research on factors and characteristics of technologies that promote trust is twofold: on the one hand, it is entitled to successfully market and launch new technologies and, perhaps, even promote brand loyalty and vendor's reputation (Gefen et al., 2008; McKnight et al., 2011; Li et al., 2008), while, on the other hand, it is important for public policy domains and economic consequences of technological ubiquity (Bodo, 2020; Mazey, 2018; Tirole & Rendall, 2017).

Simpson and Vieth (2021) state that, apart from the necessity of presence of a trust-relevant situation and strain tests, any form of trust, irrespectively of the trustee's nature, should contain three elements. "I trust he/it to do X" is the common formula that unites various trust definitions throughout scientific domains (Hardin, 2003). In this sense, the three components are (1) properties of the trustor (I/myself), (2) properties of the trust agent (he/it), and (3) the current situation (to do X). Consequently, trust in technology is defined as "one's attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004, as cited in Xu et al., 2014).

Prior research on trust in technology concentrated around individual differences (the "I" component) and, somewhat, around the trust agent's properties [e.g. national government information system study (Li et al., 2008), Microsoft Office study (McKnight et al., 2011)]. However, the third component – the situation – is ever more significant for trust prediction, since its nature and its antecedents are dynamic and tend to change over time (Mazey, 2018; Bouwman & van de Wijngaert, 2009). In fact, all three of the above-mentioned components are shifting, since current technologies are very much different from older ones; they are disruptive and pose a mediating effect on interpersonal and institutional trust as well, which was never present in older scenarios (Bodo, 2020). Hence, the dynamics of this shift should be looked into in the light of a complex phenomenon: digitalization. Essentially, scholars from various far-reaching domains discuss digital transformation and its consequences for the society on the verge of a big shift. Management (e.g. Montag & Diefenbach, 2018), marketing (e.g. Chi-Hsien & Nagasawa, 2019), public (e.g. Brynjolfsson & McAfee, 2014), governmental (e.g. Bentley et al., 2019), and various other economic and business sectors are hugely effected by new technologies.

It is important to draw the line between existing and emerging technologies, since it will be fundamental in further discussion on trust in technology. According to Mazey (2018), some examples of emerging technologies, found in the literature, include "biotechnologies, nanotechnologies, robotics, internet of things, virtual reality and genomics to name a few". The author underlines that re-engineering or upgrading existing technology (e.g., Iphone 10 to Iphone 11) on its own does not classify it as emerging, since, based on the conceptualization by Einsiedel (2008), this does not satisfy the three emergence components, which are innovativeness, revolutionary potential, and disruptiveness. Figure 1, derived from Mazey (2018) in appendices, presents the proposed set of criteria for categorizing a technology into either the existing or the emerging group. According to Bodo (2020), the number of emerging technologies in the recent years has grown to an extent that we can indeed conclude a major shift.

As with every major innovation, through its influence on business models and economic relationships, digitalization is likely to also have reshaped the very essence and form of human existence (Kraus et al., 2021). The increased pace of life, overload of information that is driven by technological advancements, embedding of smart digital devices to everyday life and new emerging technologies – which potentially mediate the way we trust each other, communicate and work – are all influencing the trust components (Bodo, 2020). That is why a more comprehensive updated view on prior models is essential. "The majority of current research on trust in technology focuses on situations that involve an individual user's interactions with it" – state Xu et al. (2014). Today, on many occasions, users do not understand the system and, consequently, do not have a chance to mitigate the risk. They may even be unaware of the full extent of their role within the technology they are interacting with or submitting their personal data to. Users are becoming "smarter" too: younger generations are referred to as "digital natives" (Dingli & Seychell, 2015), meaning that their approach to technology may be completely different. This may have significant consequences on the appropriateness of established trust models.

It is even more so since "many technologies consciously resist existing institutions of regulation and control" (Yeung et al., 2019; Xu et al., 2014; Mazey, 2018), and the current trust-production logic is demonstrating its insolvency to incorporate worldwide-scaled technological networks. Each transformation comes along with a corresponding trust crisis, which has to be addressed with the building of new institutional and societal logics that address up-to-date and context-relevant risks (Shapiro et al., 1992). Van den Dam (2017) conducted a study devoted to trust under digitalization. It turned out that in the three year time (from 2014 to 2017) consumers' overall trust decreased for all economic sectors, with digital platforms like Uber in the lead at -23%. Moreover, 50% of respondents reported to be increasingly suspicious about their personal data usage. That is why the purpose of this paper is to address the pertinence of current approaches to measuring direct trust in technology and compare the role of different types of trust predictors between existing and emerging technologies.

Literature review

In order to assess the changing antecedents of trust in technology, it is important to look at previous approaches to studying this construct. "Some trusting bases may appear to have a significant effect on trusting beliefs when tested in isolation or when a less comprehensive set of determinants is studied" – claim Li et al. (2008). In fact, multiple researchers underline the necessity of a complex model structure to arrive at thorough conclusions on technological trust predictors (McKnight et al., 2011; Lyons et al., 2020; Johnson, 2007; Garry & Harwood, 2019).

Figure 4 in Appendix B presents research directions taken in relation to trust in technology in the last decades. The majority of models, previously exploited, were concentrated around active usage of a specific technology, and, consequently, looked into the perceived ease-of-use and other properties of the software (Mazey, 2018). For instance, Davis' Technology Acceptance Model-TAM (1989), McKnight's model (2011) and Fogg's Prominence-Interpretation Theory (2003) are all based on the premise that relevance to the task, ease-of-use and certain individual differences lead to trusting beliefs or intentions of system usage. TAM and McKnight's model, which are adaptations of the Theory of Reasoned Action (Fishbein & Ajzen, 1975), were built in processional fashion, meaning that apart from the trusting beliefs, they accounted for the ways these beliefs predicted trusting intentions or the actual system usage. For the purpose of the current paper the connection between the three of them will be assumed present in the same manner (Garry & Harwood, 2019) but excluded from the studies, since the focal point of the research is the change of the objective external factors, driven by digitalization, rather than questioning the reliability of long-established paradigmatic patterns.

Since the current technological state does not let the majority of users be active, new ways of exploiting the systems lead to a relative decrease in general significance of the influence of technology's properties on trust. Therefore, the focus of the current research will lay in the realm of combining the most promising predictors from the recent studies, aligned with the theorization by McKnight (2011), Bodo (2020), and others.

Theoretical foundation

Bodo (2020), in his analysis of the current-state of trust in the developed economies and the appearance of new systematic shifts – which are occurring due to the power relocation between the market players – provides examples of the market, legal services and banking institutions as the running frameworks of control. These systems allow citizens to rely on the established rules rather than "bare faith" and provide a sense of security to the users. Ultimately, they "form a complex, mutually interdependent institutional network of checks and balances, whereby trust is produced through internal governance mechanisms, external control, and the division of power". However, when the technological advancements are making their providers extremely powerful (Schwarzmüller et al., 2017), it may become more complicated to base trust in governmental and structural assurances that are outdated, non-effective, and, therefore, unreliable on their own.

The fact that structural assurances may no longer be as valuable for trust in technology formation as were before is becoming ever more significant when considering the other side of trust – the one seen as irrational. This side bases trust on "intuition" and may change irrespectively of the objective actions and events. In this sense, risks and paybacks are often assessed through believing in fate. It is suggested (Einsiedel, 2008; Li et al., 2008) that when classical mechanisms based on knowledge and cognitive perception of risks become "unreachable" (for instance, there is no information available, or the institutions are unable to provide security and stability of the market, etc.), the "faith" gets a bigger share of the attention of a decision-maker. In terms of trust in general, the difference between the cognitive and non-cognitive drivers has been discussed through various perspectives. For example, Luhmann (2000) introduced the terms "particularistic" and "universalistic" trust. While particularistic trust is somewhat similar to Noorderhaven's "personal trust" (1992) and represents trust based on personal knowledge of the trustee and the established rules and conditions around the relationship, "universalistic" trust by Luhmann depends on the social characteristics and shared general belief about the trustee, since there is no personal experience. Other similar terms that are concerned with the same understanding of the pluralistic essence of trust are "cognitive" versus "emotional" types of it.

While contradicting Barber (1983), Lewis and Weigert (1985) argue that the rational part of trust in the works of the experts from the previous decades had largely been over-valued. In reality, the specialists claimed that restricting trust to simple expectations hindered the complete understanding of the antecedents of trust, making the analysis overly functional. According to the authors, researchers in general tended to "use methodological approaches that reduce trust to its cognitive content through psychometric scaling techniques or to its behavioral expressions in laboratory settings" (p. 975), jumping from one extreme to the other in the trust research.

In practice, Bodo claims, "the different components of trust continuously recombine, substitute, and complement each other" (p. 4), seeing the dynamics as a spectrum of trust. However, while Seligman (1997) views the actual trust to be laying somewhere in between the two extremes, Bodo suggests that the relative importance of the rational or non-rational components of trust has to be assessed contextually. Similarly, Lewis and Weigert consider "these dimensions of the phenomenon interpenetrating and mutually supporting aspects of the one, unitary experience and social imperative that we simply call trust" (p. 972).

Luhmann (2000) agrees with Lewis and Weigert (1985), who metaphorically elaborates on the dynamics between the two types of trusting drivers in the following way: "the cognitive element in trust is characterized by a cognitive 'leap' beyond the expectations that reason and experience alone would warrant. They simply serve as the platform from which the leap is made" (p. 970), thus underlining the importance of both cognitive and emotional trust to form meaningful partnerships. Apart from that, they claim that "although there are individual differences relevant to the trust factor, the cognitive content of trust is a collective cognitive reality that transcends the realm of individual psychology, and herein lies the theoretical significance that the cognitive base of trust lies in trust in trust" (p. 970). That is where the separation between faith and confidence predictors and individual differences lies. Individual differences serve as predisposition for other trust factors; confidence predictors serve as base for the "leap", while faith predictors depict the "leap" itself, or, in other words, the elements that make it possible under current circumstances. What is more, the research suggests that this difference, apart from the general trust, is particularly applicable to trust in technology.

Since we address the issue in relation to a particular subject of emerging technologies, for the sake of avoiding confusion and misinterpretations due to slight variation in the terminology meanings used by experts, we will resort to labelling the two facets of trust as "faith" predictors group and "confidence" predictors group, as referred to by Bodo (2020). According to Simmel and Frisby (2004), as cited in Bodo, the faith components represent "a non-cognitive, non-verifiable belief in some positive outcome" by the technology user, while the confidence ones are seen as "the rational, calculative assessment of risk, and the ability and agency of the parties involved to reduce vulnerability". In this sense, for the purpose of the study, the model's variables will be subjectively divided into the "faith" or "confidence" predictors on the basis of their essence and the nature of their formation. Although these notions may differ between people, we believe this general subdivision to be relatively representative. In order to demonstrate that, pre-tests upon the subdivision will be subsequently carried out.

As we see from the previous research on trust in technology, it has been largely concentrated on the "constancy" parameter of the technology itself or its characteristics (McKnight et al., 2014; Li et al., 2008). However, such emerging technologies as machine learning, for example, may produce different results for different users based on the entry data. It comes up with a probabilistic result that represents a personalized suggestion. According to Csigó (2017), the absence of the actual shared universal trust signals makes the users guess the reliability of the system by some abstract "Keynesian beauty contest" or "speculative bubble".

In relation to that, the faith-confidence spectrum plays a vital role in identifying which of the sets of parameters will be more or less influential under the particular given circumstances. However, there may be a general outlook of the predictors more specific to the emerging versus non-emerging technologies. Trust in emerging technology is likely to have different prenominal drivers than trust in the existing ones. This question has lately been addressed by a number of researchers (Mazey, 2018; Li et al., 2008) that agree on the experimental evidence that "the relationships in the context in emerging technologies are different and perhaps more critical than those in the context of non-emerging technologies" (Mazey, 2018; p. 25). Therefore, the following exploratory research question (RQ1) is formulated:

RQ1: Is there a significant statistical difference in relations between the model variables, and, in particular, between the faith and confidence predictors, and their effects on the trusting beliefs when analyzing the existing/emerging technologies?

Individual differences

Faith predictors, as mentioned above, are generically considered very important in situations when there is not enough reliable information or experience related to the trustee. The non-verifiable and non-cognitive side of trust-formation has some significant elements that predict if the faith will eventually occur. In other words, people resort to heuristics to help them navigate their decision-making processes if they have little knowledge about the issues involved (Merk & Pönitzsch, 2017). According to Midden and Huijts (2009) or Griffin et al. (1999), one of the aspects that create a predisposition to unconsciously behave in a certain way is concerned with the people's individual differences.

Individual differences, applied to trust research in general, have been studied by several scientists. For example, Lyons et al. (2020) in their experiment demonstrated that the participant's agreeableness and intellect (parts of the Big 5 of personality assessment criteria) and PAS (Perfect Automation Schema) that, in brief, represents the participant's predisposition to high expectations and all-or-nothing beliefs, had a significant impact on the autonomous robotics technology acceptance. Agreeableness and high expectations were associated with higher trust, while all-or-nothing beliefs, in contrast, led to lower trust in the given technology. However, contrary to the initial hypotheses, conscientiousness, extraversion and neuroticism did not demonstrate any relation with trust formation.

There were also attempts to identify which factors may influence the formation of certain personality characteristics, attitudes and lifelong beliefs on technologies' general reliability. For instance, Anderson et al. (2011) looked into the educational system and mass media as possible predictors of the formation of individual differences between people, which led to trust in nanotechnology. Using Swidler's "tool kit" model, Peters et al. (2007) demonstrated that cultures might predict attitudes towards certain emerging technologies (on an example of biotechnology). The influence of cultures in this relation is also underlined by many trust-studies' pioneers of the 20th century (see e.g. Sullivan & Nonaka, 1986). Luo (2002) also pointed out the significance of socio-economic factors, such as norms and culture. That is why identifying origin/belonging to certain cultures in the studies on trust is vital.

Other studies concentrated on discovering a relation between trust in technology and age, level of education or gender. Bouwman and van de Wijngaert (2009) identified a slight but significant relationship between the participant's gender and their likelihood to engage in the usage of a new previously unfamiliar technology. Abu-Shanab (2011) showed a relation between education and the behavioural intention to use a technology.

However, it is important to state that some researchers criticize studies that concentrate around one or several individual characteristics of the participants only, without applying them to a more complex, thoroughly analyzed model. In fact, according to Li et al. (2008), when studied as part of a bigger model, some individual characteristics lose significance and are, therefore, subsequently excluded. Age, gender, personality and other similar constructs usually fall under this category. Nonetheless, some individual differences, more related to trust and faith in the world, have proven to be influential on technology acceptance. Further, the description of individual predictors and the relations between potential variables will be looked into in more detail.

Faith in humanity

One of such characteristics is general faith in humanity. It is defined by McKnight et al. (2011) as the participant's belief that "Others are typically well-meaning and reliable", in other words, it represents the person's belief in the fact that by default people are usually complying with the "rules of the game" and have the best interests in mind.

It is different from the McKnight's definition of Trusting Stance, which, in turn, suggests that people, irrespectively of what they think of others, prefer to act as if others were reliable. It is also different from Mayer et al.'s (1995) Propensity to trust or McKnight's Disposition to trust, since these definitions account for a willingness to trust others. While intentions to trust people in general are likely to be supported by the Trusting Stance or the faith in humanity, they are not a necessary step for having trusting beliefs. The Trusting Stance is a construct that is experientially-based and brings additional value to the faith in humanity under circumstances where certain economic, political and social issues of the current context are reported to be disturbing or unstable (Li et al., 2008). However, in our research, due to the model's complexity and the possible errors and fatigue caused by the length of the questionnaire delivered to the participants, we will not use the Trusting Stance construct. That is why, despite slight variability of definitions, for our research purpose we will concentrate on the faith in humanity solely, as the one better fitting the model.

Trusting personality variables, as referred to by Alarcon et al. (2016), are relatively stable individual characteristics, which develop in childhood. Regarding that, we may look for relations that faith in humanity may have with other trusting predictors.

Mazey (2018), through conducting a PLS-SEM analysis on both emerging and existing technologies, supported the theory that the faith in humanity is strongly related with the economic environment. What is more, she reveals that, according to her studies, "faith in humanity can be used to compensate for low levels of knowledge-based trust which causes uncertainty around a technology's functionality, effectiveness, reliability, or even data integrity" (p.132). This fact is extremely important in the light of the emerging technologies. Gill et al., (2005), as cited in Alarcon et al. (2016), also theoretically support it, stating that it "may serve as information driving one's evaluation of a novel situation as it is related to trust when the situation is ambiguous" (p.310).

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Faith in humanity, according to Tweed et al. (2020), “though seldom mentioned, already implicitly pervades much of positive psychology” (p. 298). In their research of the construct, they have discovered that those who are generally more prompt to have this quality are more likely to perceive the world and their own life situation as a better and more stable one, in comparison to those who do not possess faith in humanity. The authors also suggest that these people have a more positive mindset and are less likely to get involved in sharing beliefs about conspiracy theories.

Perceived power asymmetry

As mentioned earlier in the introduction, the new digital reality is completely different from the previous stages of technological developments, since new big players appear to dominate the digital markets. Vendor-based trust is defined by Thatcher et al. (2013) as “beliefs consumers have in a vendor’s competence, benevolence and integrity”. McKnight (1998) suggested that vendor-based trust is influenced by a person's faith in humanity. Naturally, when a person trusts in the safety of transactions in the market, it raises the level of trust or, in other words, the disposition to trust in the sellers, even when – and especially when – there is no prior experience or knowledge about it. To demonstrate this point of view, we make an example of the study, conducted by Carbonell et al. (2019), where users had to look at various online platforms with reviews and identify if they trusted in the seller. As reported by authors, “the trust cues were only relevant in interaction with variables that measure trust in the Internet as a safe environment for making monetary transactions”. What is more, Sheth (1983) and Williams et al. (1998) separately arrived at the same conclusion that individual’s beliefs about safety of the economic environment they are in will impact vendor-based trust in technological context because it entails the feeling of security or lack of it regarding how vendors perform, their interests and priorities etc.

In relation to vendor-based trust, researchers have previously studied various aspects of this construct, starting from the classical competence, benevolence and integrity perceptions (see e.g. McKnight et al., 1998; Mazey, 2018), to inclusion of scientifically specific cases like their website quality or online reviews (Salo & Karjaluoto, 2007). However, as read in Tirole and Randall (2017), vendor’s reputation in the current digital reality is not always a predictor of trust. The problem is that the business models have drastically changed in the last years, which leads to overflow of information and available agents on the markets. If some 30 years ago a buyer willing to listen to some music would only have several options of nearby shops and would make a choice only based on the price/quality ratio and personal taste, nowadays they could get access to a variety of digital libraries from any part of the world. Digital commodities are changing the way players on the markets communicate, make transactions and develop trust.

One of the most significant shifts is concerned with the appearance of platforms as a new type of business models. Companies such as Google, Meta, and Uber have started with a single digital idea that made people's lives easier. Tirole and Randall underline that as more information is available on the market, the more platforms are on the rise. This happens because they have the ability to structure the environment and take up a role of mediators in two-sided market transactions, which makes it more convenient and easy for all the parties involved (Möhlmann, 2015). Two-sided markets are those where there is a mediator between a buyer and a seller, which performs monitoring, signaling, reviewing, and even regulating functions, while creating its own rules and standards of usage. As stated by Bodo (2020), "We may not be able to rely on the reputation of an anonymous user, but we may have some confidence in the technology to force the counterparty to respect a set of pre-defined rules". It is important to notice that this kind of regulation setting is applied to the actual technology purchase and usage rather than general laws and institutional regulations. That is why this concept is differentiated from the institutional-based trust.

This point is of upmost importance since the users of the platforms do not have much of a choice, nor power to change or settle the rules. Garry and Harwood (2019) refer to this problem, stating that "when data and information flow is persistent – for an individual actor there is ultimately only one way to have any control over this and that is to disengage with the entire system" (p. 416). In the current reality, it may mean to lose significant amount of time, meaningful relations, or even personal identity (according to identity commitment to technology theory by Johnson, 2007). Market power of the platforms grows even more, since they expand their businesses building a whole ecosystem around its services, where a buyer cannot use one service without another. In theory, a large number of projects and governmental regulations are set to navigate and mediate this dynamic. For example, the Platform for Privacy Preferences Project by World Wide Web Consortium or a private organization named TRUSTe declare a set of guidelines for private information usage (Salo & Karjaluoto, 2007). However, according to Tirole and Randall (2017) until now the regulations and the power of such projects and governmental incentives are not effective against big digital market players.

Platforms collect personal data extensively and may use it for their personal benefit. They signal that it increases the amount and quality of personalized services and offers, which holds the customers' interests at the heart of the business. However, "the lack of transparency of the process that converts input data into decisions carries the risk of potential algorithmic bias, discrimination, and unaccountability" (p. 11), states Bodo (2020), referring to claims by Poort and Zuiderveen Borgesius (2019).

That is why the question of power asymmetry is getting a hold on the modern digital users. While trust-mediators, such as digital platforms, are dominating the markets, they "have little incentive to take responsibility for any breach of trust in the interactions they structure" (Bodo, 2020). What is more, Orekhova & Kiseltsyn (2019) in their economic model discovered that "the higher the level of power asymmetry, the faster the economic growth in the industry market" (p. 131), which is why the situation is likely to keep the same dynamic of development.

Apart from that, the changing business models make it very hard to identify who, in fact, is a "vendor". Everyone has always known that Microsoft Word was created by Microsoft, so users could develop a particular type of experience-based beliefs about the company. At present, platforms generate the trust themselves, share it with the vendors and clients, and regulate the system. In the analysis by Bao and Chen (2012), researchers state that there are no more singular service providers, on which customers focus trust decisions. Bodo (2020) underlines this aspect too by saying that "the use of digital technologies by private and public entities creates new uncertainties, conflicts of interest, and modes of operation; it restructures values and ethics. All of these affect these abstract systems' trustworthiness and their ability to produce trust" (p. 16). After conducting her analysis, Mazey (2018) also excluded the vendor-based trust from emerging technologies trust formation model.

Taken holistically, the vendor-based trust currently is moving toward system-based trust (Bodo, 2020) that is built within the market. What is more, faith in humanity is likely to shape the extent to which the person perceives the unfairness on the market. That is why it is suggested to incorporate the perceived power asymmetry variable into the model. Although it is a new point of view on the technology trust predictors, we believe that it might substitute the classical vendor-based trust construct under the current circumstances, depicted above. If tested to be valuable, it could later be studied more closely and be solidly theorized. Unfortunately, it exceeds the scope of the current work.

The assumption that we are making in the research, tied to a technological context, defines the perceived power asymmetry as "an individual's belief that he/she is unable to control or negotiate the rules and conditions of technology usage, nor quit using the technology". Therefore, hypotheses H1, H1a are formulated:

H1: There is a significant negative relation between faith in humanity and perceived power asymmetry

H1a: The strength of the relation is significantly bigger for the emerging technology than for the existing one

Concern about privacy

The questions raised above lead us on to talk about the privacy concerns in more detail. According to Pavlou (2014), "consumer trust could be described as a function of the degree of risk involved in the situation". Researchers have studied various risk domains within trust in technology, and concern about privacy seems to be one of the predominant risks that worry a great number of people (van den Dam, 2017). Garry & Harwood (2019) define privacy as "control over information disclosure and use specifically in relation to the duplication and sharing of information for secondary use".

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Schlosser et al. (2006) demonstrated a negative impact of concern about privacy on trust in e-commerce. Garry and Harwood (2019) supported the same effect for the IoT technology. What is more, it was empirically proven that concerns about privacy are dependent on both individual differences and the perceived economic environment (see e.g., Klang, 2006; Mazey, 2018; Kumaraguru & Cranor, 2006, Bansal et al., 2010). What is more, Thaw et al. (2009) demonstrated that threat to privacy significantly decreased the number of online transactions within the e-commerce context. Therefore, if the individual's perceived power asymmetry is relatively big, he/she is more likely to have privacy concerns.

Some studies found a more significant relation between the benefits of technology (for example, personification) and its actual usage in comparison to the relation between the latter and the risks of using the technology (Stevenson & Pasek, 2015). However, they suggest that this result may be determined by the fact that "if individuals are largely unaware of the degree to which information about them is collected and used to customize the content they see online, and then costs such as reductions in privacy have little impact on attitude formation". However, regardless of the amount of knowledge about the process, if present, concerns about privacy from using technology directly predict the trust in it.

Bradford et al. (2020) support this relation between the proposed variables by stating that "the organisations and institutions implementing technologies, can be central in shaping people's assessments of the associated risks and benefits, and hence their willingness to support or oppose the introduction or uptake of, for example, gene-splicing, nanotechnology, or novel power–generating technology" (p. 4). They also identify that, in concern with live-recognition, privacy concerns served the most important predictor that motivated acceptance or rejection of this technology. Thus, the hypotheses H2, H2a, H3 and H3a are proposed:

H2: There is a significant positive relation between perceived power asymmetry and concern about privacy

H2a: The strength of the relation between perceived power asymmetry and concern about privacy is significantly bigger for the emerging technology in comparison to the existing one

H3: There is a significant negative relation between concern about privacy and trusting beliefs in technology

H3a: The strength of the relation between concern about privacy and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

Social norms

Subjective norms in technology acceptance, as defined by Mazey (2018) on the basis of a preliminary literature review, are "normative beliefs held by individuals about people in society that they consider important, and people's desire to use a certain technology or reject using it according to others' expectations about how they should act and behave". Classical definition of social norms by Ajzen (1991) is a "person's perception of the need to behave in a certain way due to social pressure". Ever since social norms were added to the classical TAM models (see e.g., King & He, 2006; Holden & Karsh, 2010), they started to enter all the following extensions of previous technology acceptance models or new models, created independently from the former ones. The first ones to test social influence within the TAM frame were Davis and Venkatesh (1996). The theorization that social norms will shape the behavioral intentions in technology usage was based on the Theory of Reasoned Action (TRA). Another theoretical base, provided by Li et al. (2008), encompassed internalization concept, which is a process in psychology when a person makes other people's beliefs her/his own. Internalization, also tied with Kelman's effect, suggests that subjective norms directly influence one's attitudes and later, one's intentions.

Multiple researches and analyses have proven its relation to trust in technology, trusting beliefs or trusting intentions. For example, Li et al. (2008) confirmed that subjective norms were the greatest predictor of trust. Ceseracciu et al. (2014) showed that they mediated trust and intent, especially in situations when vendor was unfamiliar or there was no previous experience using a technology. However, the researchers concluded that when vendor-based trust was high, the effect of subjective norms became less significant.

However, having noticed that social norms construct used to be classified or defined differently throughout the thematic studies, Cialdini and Goldstein (2004) have developed a theory of subdivision of social norms into two categories: injunctive (ISN) and descriptive ones (DSN). Injunctive social norms (basically, subjective social norms that were referred to above), in fact, were based on perceived expectations about one's actions from significant others, while descriptive social norms addressed the question of if the significant others were performing the action themselves. These two constructs are very different in nature and, according to the authors, should be studied separately. The impact of descriptive social norm, individually, was studied in application to technology for social networking and was proven to be significant. Other examples of usage of descriptive social norms represent the willingness to share personal information for personalized services in e-commerce setting if people knew others were giving this information (Chen et al., 2012; Cheung et al., 2011).

It is important to notice that this separation between injunctive and descriptive social norms is also vital in terms of subdivision into faith or confidence predictors of our model, since injunctive social norms are generally subconscious and subjective, and descriptive norms are objective and verifiable. We also find that injunctive social norms are likely to show more significance as a variable when applied to emerging technologies, since "prior experience might already suffice to shape continuous use decisions" (Beldad & Henger, 2017, p.890).

Mazey (2018) also suggests that there is a relation between subjective norms and threats to privacy, based on empirical data and logical thinking. However, while agreeing with the fact that social norms are likely to influence technology acceptance or rejection, we assume that this construct is a separate category within the faith and confidence predictors that does not have a direct impact on concerns about privacy. That is because believing in others wanting the person to use technology or using the technology themselves does not diminish the fact that the fear or concern about the risk is still present. The following suggested hypotheses are H4, H4a, H5, and H5a:

H4: There is a significant positive relation between injunctive social norms and trusting beliefs in technology

H4a: The strength of the relation between injunctive social norms and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

H5: There is a significant positive relation between descriptive social norms and trusting beliefs in technology

H5a: The strength of the relation between descriptive social norms and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

Calculus-based trust

Another concept that we consider important for the current research is the calculus-based trust, which lays in the confidence predictors category, since its representation is concerned with the most objective and rational part of technology acceptance beliefs formation. It originates from transactional costs economists' ideas that players on the market are rational and pursue their own personal self-interest (Lewicki & Bunker, 1995). In trust research, it assumes people's beliefs that other market agents and players will not engage in opportunistic behavior if there is no objective benefit he could obtain from doing so (Shapiro et al., 1992). Although typically applied to volitional agents in interpersonal or organizational context, this construct has also been studied in connection to technology (see e.g., Gefen et al., 2003; Marcella, 1999; Li et al., 2008).

When studying initial technology trust, Li et al. (2008) discovered that calculus-based trust predicted beliefs about technology acceptance. Gefen et al. (2003) also found this relation significant in their online vendors study. Paul & McDaniel (2004) have argued that calculative-based observations also predict the initial trust in technology. In fact, they discuss the general empirical rule that it is applicable to any sort of relation to beliefs or intentions as long as the trustee is vulnerable in the system. Since users are very vulnerable in front of the current system and have to bear privacy risk and other types of risks when dealing with technologies, it is likely that the cost/benefits calculation will play an important role in forming their trusting beliefs. Therefore, the definition of the calculus-based trust in the given context goes as follows: "the acceptance of a certain level of vulnerability based on the calculated costs of maintaining or severing a relationship", which in our case is a relationship with technology (Williamson, 1993). Therefore, H6 and H6a are developed:

H6: There is a significant positive relation between calculus-based trust and trusting beliefs in technology

H6a: The strength of the relation between calculus-based trust and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

Technological savviness

Another variable that, in different forms, has been used in a variety of studies (Mazey, 2018; Beldad & Henger, 2017; Garry & Harwood, 2019) is initial familiarity with the system. However, taken that we are targeting our analysis at the emerging technologies that are quite complex and require a thorough understanding of IT in general to understand the system, familiarity may have to be looked at from a different angle. Researchers who examined initial trust in technology usually tended to exclude this variable from their models (Li et al. 2008), motivating it by the fact that the influence of familiarity is controlled by participants previously not having had experience with the technology.

While naturally this assumption may seem logical and even be true with earlier studies and models, Garry & Harwood (2019) in their analysis underline an important point, which states that nowadays electronic and technological systems tend to follow a similar logic. This means that, even though a person is not familiar with the technological "inside-out", he/she may be able to grasp the idea about the technology on the basis of previous technological experience with similar systems. The authors indicate that technology familiarity "is not determined by interactions with a single device or touchpoint nor by a brand that bounds a service context but is embedded within it indicating the nature of trust in such systems. Such embedded trust is neither a consequence of nor an antecedent to the service experience per se but incorporates agent-based trust and trust acquired from the behaviours of other similar service systems" (p. 417).

In regard to this, being able to gauge the performance of the technology by previous experience with other IT interfaces in general might influence trust in emerging technologies even if the user is passive and does not understand how the system is operating. Various definitions that have been used interchangeably throughout the studies on Information Technology were adopted in literature. For example, IT literacy (Ferro et al., 2011), digital competence (Calvani et al., 2012) and others. However, in light of the current study, the term that best incorporates experiential-based familiarity with technologies is technological savviness. This term is described as "an individual characteristic of a person that shows he/she is informed about or proficient in the use of modern technology".

What is more, Wang et al. (2013) underline that this notion is extremely important for modern technologies' research. They explain it in a following way: "some of the theories such as the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (Davis, 1989) are based on the assumption that users tend to resist or at least have some difficulty accepting new technologies and systems" (p. 412). In fact, in our current reality, "digital natives" are eager to try new things and are computer literate since a very young age (Prensky, 2012). Wang and colleagues moved on with their research to prove that "digital immigrants" – people who adopted technologies when they were adults, however, sometimes exhibit the same easiness to use technologies. Despite being an important theme for further research, predictors of digital literacy go beyond the scope of current paper. Nonetheless, this variable's significance for the emerging technologies acceptance should be recognized.

Technological savviness was shown to influence technology adoption (for example, sharing of autonomous vehicles research by Lavieri et al., 2017). Although Garry and Harwood (2019) also made an additional assumption that concerns about privacy were negatively correlated with experiential-based performance assessment, with the mediation of tech-savviness, in reality this relation failed to reach significance.

Institutional-based trust

Government and other institutions traditionally mediate the relationships on markets: they establish rules, norms and practices that regulate and protect from unfair treatment or exploitation of personal resources. All these examples may be referred to institution-based trust dimension. McKnight et al. (2011) point out that this construct consists of two separate entities – situational normality (SITNOR) and structural assurance (STRASS). They also define the terms in application to technological context.

According to it, SITNOR may be described as "the belief that success with the specific technology is likely because one feels comfortable when one uses the general type of technology of which a specific technology may be an instance" (p. 5).

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On the other hand, STRASS refers to "the belief that success with the specific technology is likely because, regardless of the characteristics of the specific technology, one believes structural conditions like guarantees, contracts, support, or other safeguards exist in the general type of technology that make success likely" (p.5).

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Such variables have been used in relation to trust-formation research massively (see e.g. Garry & Harwood, 2019; Mazey, 2018; Xu et al., 2014, etc.). Mazey (2018) suggests that "In the case of emerging technologies specifically, laws and regulations are often too slow to adapt to adequately protect individuals in a timely manner", and, therefore, institution-based trust dimension might not be as effective. However, Bradford et al. (2020) hold a view that it is still predictive of trust formation. Meanwhile STRASS is an objective, more rational construct, which is referred to the confidence part of the predictors, SITNOR appears to be more suitable for the faith predictors category (Bodo, 2020), which is why the two items of this construct will be specifically looked at in separation.

We also hypothesize that one of the parts of institution-based trust, specifically situational normality, will be positively influenced by faith in humanity and technological savviness. McKnight et al. (2011) theorize that there is correlation between faith in humanity and institution-based trust in their research. Li et al. (2008) and Spadaro et al. (2020) found a significant effect of faith in humanity on institution-based trust as well, which allows us to move forward the hypotheses H7-H10a:

H7: There is a significant positive relation between faith in humanity and situational normality (applied to technology)

H7a: The strength of the relation between faith in humanity and situational normality (applied to technology) is significantly bigger for the emerging technology in comparison to the existing one

H8: There is a significant positive relation between technological savviness and situational normality (applied to technology)

H8a: The strength of the relation between tech-savviness and situational normality (applied to technology) is significantly bigger for the existing technology in comparison to the emerging one

H9: There is a significant positive relation between structural assurance (applied to technology) and trusting beliefs in technology

H9a: The strength of the relation between structural assurance and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

H10: There is a significant positive relation between situational normality (applied to technology) and trusting beliefs in technology

H10a: The strength of the relation between situational normality and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

Technology trusting beliefs

The dependent variable – technology trusting beliefs – will be studied along the theories developed by McKnight et al. (2011), Mayer et al. (1995), Mazey (2018) and other researchers who claim that technology may be studied as a separate trust object. Although the discussions about the nature of technological trust – either behavioural or object-based – are still present in the literature (see e.g. Gefen et al., 2008), most experts conclude that people, in fact, place trust in technology as an object itself. Mazey (2018), following the idea of McKnight et al. (2011), suggests that people may trust in technology while still considering trust in technological providers or institutions that operate it, seeing the people behind the technology. Bradford et al. (2020) agree with this point of view, stating that organizations and institutions can be central in steering people in the directions of usage of novel technologies.

In regard to this, studying the influence of the variable, introduced in the model above, seems logical, since it represents the most holistic and complex approach. Trust in technology, by Mayer et al. (1995), is defined as the "willingness to be vulnerable and accept risks relating to the use of an information technology artefact". McKnight et al. (2011) and, later, Mazey (2018), Xu et al. (2014), Lyons et al. (2020), and others, used the following components of trusting beliefs in technology, as adapted from the people-to-people trusting beliefs: (1) Competence – having the skills and ability to do a task; (2) Benevolence – being of a caring, considerate nature with intentions of goodwill; (3) Integrity – acceptable principles, being consistent in words and deeds, having a good reputation and sense of justice. Figure 2 in Appendices contains the full list of developed hypotheses.

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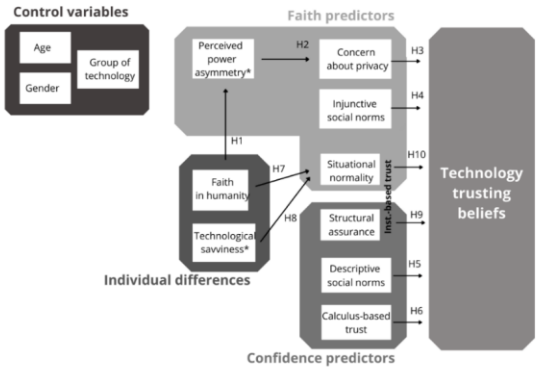
Proposed research model



Methodology and data collection for Study 1

Research design and methods

The overarching purpose of the current paper is to identify antecedents of trust in technology under digitalization, and further analyze if there is any statistically significant difference between the factors that influence emerging technologies versus ones that were launched and commercialized long ago.

To support a more natural environment, real technologies were selected to test the hypotheses. According to Mazey (2018), as seen in Figure 1 in Appendices, an emerging technology must possess three major characteristics: innovativeness, revolutionary nature, and disruptiveness. In her study, she conducted a primary experiment to test a number of technologies, trying to identify which ones belong to the category of existing ones, and which ones do not. Based on works of Mazey (2018), Garry & Harwood (2019), Bodo (2020), Lyons et al. (2020), McKnight et al. (2014), and others, it was concluded that a more realistic interpretation of the categorization could be obtained if some of the previously studied technologies would be taken for observation. In particular, bionano technology, which was reported by many previously mentioned authors to be an emerging technology, was tested in the experiment by Mazey (2018),and proved to satisfy all the emerging technologies' criteria. As mentioned by McKnight et al. (2014), there is a "surprising" variety in trust shown by people to different technologies. This is why it is decided to control for the potential technological specificities by creating two conditions: one that would steer the respondents to believe bionano technology to be emerging, and the other one, which would showcase it as an existing technology. Mazey's approach to degree of emergence criteria testing is quite new and, thus, requires additional studies with replication of the results. However, it goes beyond the scope of the current master's paper, since it aims at primary identification of phenomenal patterns rather than testing of an existent theory. Nonetheless, in order to ensure technology's degree of emergence perception, a face value manipulation check was added to the questionnaire.

Despite the fact that trust may be perceived and approached differently between individuals, the relative novelty of research on trust in emerging technologies poses doubts as to potential significance of qualitative approach to contemporary studies. According to Yin (2003), such research design aims at understanding the "How" and "Why" of the processes in the society, while the questions of the current paper represent a more basic objective of uniting the "scattered evidence" (Mazey, 2018), present in literature, to study the "What" of emerging technology trust formation.

The data on the independent variables (IV) – the set of individual differences – was collected first, followed by a randomized allocation of participants between the "control" (existing technology) and "treatment" (emerging technology) conditions, after which a set of further questions about faith and confidence predictors of trust was asked with regard to the information, displayed about the specific technology. Lastly, the trusting beliefs in the technology were assessed as the DV. Apart from that, the research controls for potential extraneous variables, identified in the literature, such as participants' age or origin.

The multi-stage regression modelling method was chosen for data analysis, using partial least squared structural equation modelling (PLS-SEM) to test hypotheses 1-10. Matthews et al. (2018) argue that PLS-SEM is a great technique to evaluate complex models, since it is able to assess the latent variables along with the relationships between them through an iterative approach. This allows maximizing the explained variance of constructs. Lowry & Gaskin (2014) called for a broader application of PLS-SEM analysis in IT domains specifically, due to its ability to "capture the bigger picture". Authors also suggest that this analytical method is preferred when the nature of research is exploratory and the "supporting theory is less developed".

In order to answer the RQ1, multi-group analysis (MGA) using partial least squares path modelling (PLSPM) is further proposed. According to Cheah et al. (2020), it is an effective way to measure moderating relations within complex models. It is especially valuable to study heterogeneity effects, such as effects of gender or age, and differences between pre-defined groups, as in the case of current study with emerging versus existing technologies conditions (Matthews et al., 2018). It is also preferred when the nature of research is exploratory, since it runs comparisons through iterative approaches between every relation in the model and highlights the presence of statistically significant differences.

Instruments

Following the proposed research model, all constructs were adopted from prior literature. Since the model was based on the original variation by McKnight et al. (2011), most constructs was adopted from their research, since they were reported to consistently demonstrate adequate reliability in previous studies on technology acceptance. Measures for faith in humanity and trusting beliefs in technology were adopted from Li et al. (2008), since the second-order formative constructs were believed to hold a better construct validity in comparison to other options. Technological savviness as a newly-proposed construct in trust in technology research was adopted from Parasuraman (2000), while another freshly-introduced variable – perceived power asymmetry – was drawn from Wang (2011) and modified slightly to fit in the technological context. All items (expect for the control variables) were assessed on 1-7 Likert scales anchored by (“Strongly disagree” and “Strongly agree”). Gender was measured with a dummy variable (0 = Male; 1 = Female), age was measured in years. Figure 3 in Appendices highlights all constructs’ operationalizations, respective adopted scale items and their source, along with the Cronbach’s Alphas each of them demonstrated in prior research.

The web-based questionnaire, created using Qualtrics platform, took around 10 minutes of time to complete and consisted of six sections presented to participants in the following order:

a. ***Consent form.*** Participants received information about the current research and data collection procedures being anonymous. They also read other specific instructions about the survey and had to confirm their voluntary participation and satisfaction of the age requirement.

b. Demographics. Three demographic parameters were studied, namely, age, country of nationality (origin), and gender. All questions had an option to not disclose the information, should the participant have been uncomfortable with it.

c. Individual differences (IV). This block was shown to all participants and contained questions on faith in humanity and technological savviness.

d. Manipulation/treatment. This section presented a short video fragment on the technology. The condition block – emerging or existing – was shown to participants randomly. The questionnaire included a time code to ensure every participant watched the video, meaning that it was impossible to proceed to further questions before the time required to watch the fragment passed.

e. Manipulation check. In order to ensure manipulation validity (Matthews et al., 2018), several measures were taken: firstly, a Boolean instrument question "Did you manage to watch the provided video and did it display correctly?" was introduced, followed by a question to indicate one type of information provided in the video (there were three options given, only one of which was correct). Those who did not pass the manipulation checks were further excluded from analysis. Also, a face validity check was introduced with a question "To what extent do you find the technology emerging?" on a 7-points Likert scale for both groups.

f. Covariates and DV. Further, a set of questions with regard to the shown technology was asked. This included items on structural assurance, situational normality, descriptive and injunctive social norms, calculus-based trust, perceived power asymmetry, concern about privacy, and, finally, technology trusting beliefs. The items were presented in random intermixed order, as suggested by Mazey (2018) and Goodhue and Loiacono (2002), since grouping of questions in IT research is not advised due to "artificial inflation of reported reliability" and encouragement of hypothesis guessing, which results in inflated strength of links between variables. Due to a high number of matrix questions, an attention check was added with a randomly placed item "Please select 'Strongly disagree' on this question so we know you are paying attention". Participants who failed to pass the check were also further eliminated from data analysis.

g. Debriefing. Since participants did not understand the full nature of the study and presence of several conditions beforehand to avoid biased answers, a debriefing technique was used in the end, which presented this information in a concise way.

Treatments

As mentioned in Garry and Harwood (2019), traditional approaches to manipulating technological nature are not appropriate in the current digital reality due to the complexity and novelty of modern devices and software. To address this issue, authors propose the filmic storytelling approach (Schembri & Boyle, 2013). The treatments for current research were presented in the form of demonstration of the technology and brief introductory information on its essence, spheres of usage and applications, and potential threats those could pose for one's privacy. In order to develop the videos, information from several web-sources was collected on the chosen technologies and compiled into short video scripts. The graphic images were also taken from free publicly available sources online (Canva free stock, Youtube, etc.). The Focos Live tool was used to develop the video fragments. The full scripts, along with the links to final versions are presented in Figures 4-5 in Appendices. It was important that the script itself or the image did not cue or frighten participants, but instead represented an actual realistic picture, using neutral language and presenting style (Garry & Harwood, 2019), and that both conditions were described equally well, which is why the wording was thoroughly analyzed and made as close between conditions as possible.

Pre-tests

As the theorization of the model and the essence of the current research are largely of an exploratory nature, it seemed essential to conduct several pre-tests that would highlight any potential inconsistencies or problems participants might face with the questionnaire, as well as to confirm the face value of faith and confidence predictors and adequacy of the utilized instruments.

Firstly, the main study's questionnaire was pre-tested using qualitative approach, namely unstructured interviews, with a convenience sample (N = 12). To avoid carry-over effects, participants who took part in the first pre-test were not recruited for further studies. During this pre-test, participants were asked to fill in the full-length questionnaire in Qualtrics, while being monitored by the interviewer. The comments and potential pain points, demonstrated by the subjects, were taken down, as a result of which slight modifications were made to the questionnaire and treatments. In particular, the attention check was introduced, since participants commented on the survey's lengthiness. Nonetheless, the mean time taken for questionnaire's completion was equal to 9.5 minutes, which is considered adequate for web-based surveys (Goodhue & Loiacono, 2002).

Finally, another pre-test was conducted on a different convenience sample (N=15). It focused on the face validity of placing constructs between faith and confidence categories, testing the theorization by Bodo (2020). For that reason, a simple web-based grouping survey was created in Qualtrics, which asked participants to arrange the constructs into one of the two groups: faith predictors or confidence predictors, providing definitions of each of the variables and the groups (following guidelines by Nevo, 1985). As a result, predicted allocation between categories, which had been developed based on prior literature, was fully supported. This fact allowed researchers to move on to Study 1 data collection procedures.

Sample and data collection

The first study recruited 301 participants. The sample was non-probabilistic, since the questionnaire was taken by students of Lisbon Catholic University. The process was organized and monitored by the Laboratory of Experimental Research in Economics and Management (LERNE). The inclusion criteria for the sample was set for English-speaking students over 18 years of age. There was no missing data in the final dataset. Further, 50 responses were excluded from the study due to failed attention or manipulation checks, which resulted in 251 unique answers. This is an adequate amount of respondents for statistical power and external validity of the PLS-SEM model, judged by the inverse square root method of minimal sample size calculation (Kock & Hadaya, 2016), considering a 5% significance level and an expected minimum path coefficient in a range of 0.11-0.2, which calls for >155 cases. The distribution between conditions accounted for 128 responses on the existing technology group and 123 responses for the emerging technology group. According to Winson Van Voorhis and Morgan (2007), a between subject design that measures group differences should have at least 30 participants per cell, which makes the current sample appropriate for the study's objectives.

The study included participants from 31 countries, in particular, Germany (41.2%), Portugal (25.3%), Italy (8.3%), Austria (2.7%), France (2.7%), and others. 241 of the respondents had finished Bachelor's degree, while the remaining 10 had Master's degree completed. 51% of the respondents were male and 49% female, the non-binary/other genders were not present in the sample. Participants' age ranged from 20 to 28 years old (M = 23.2, SD = 1.66).

Data analysis

Firstly, raw data from Qualtrics platform was extracted to Microsoft Excel, where the cleansing procedure was conducted. Some variables were reverse-coded, following Figure 3**.** The data was then prepared for import to SMART PLS 4 software, which was used for analysis. The complexity of the model constructs meant that there was a need for addressing second-order variables (i.e. for faith in humanity and trusting technology beliefs). Therefore, the procedure for the two-staged approach was completed: the latent variable scores for the respective second-order variables were taken to Excel and added as separate indicators to the original data set.

Further, path coefficients between model variables were calculated using a path weighting scheme with a standardized type of results. Later, control variables were tested for moderation effects, applied to the DV. Where appropriate, the bootstrapping procedures on 5000 subsamples, run with the bias-corrected and accelerated (BCa) confidence interval method and two tailed tests with a significance level of 0.05, were carried out (Garson, 2016; Mazey, 2018).

3.2. Manipulation validity

As mentioned earlier, several measures were taken in the study to ensure manipulation validity, as recommended by Straub and Gefen (2004), including the Boolean instrument check for video play, the question on the types of information present in the videos, and the attention check. Moreover, it was important to ensure that the manipulation with the grouping of technologies into emerging/existing conditions was valid, which is why the data on the questionnaire item "to what extent do you think the technology is emerging?" (7-points Likert scale) was later analyzed using independent sample *t*-test.

The results of this procedure showed no significant distinction between groups' means, with $t\ (199) = -1.92$, $p = .056$. The emerging technology condition ($M = 5.31$, $SD = 1.15$) and the existing technology condition ($M = 4.96$, $SD = 1.68$), thus, cannot be further compared using PLS MGA, since it requires statistically significant heterogeneity of groups. We suppose that the manipulation did not work because the participants did not believe bionano technology to be widely used and accessible (because in reality it is not). Probably, the sample's previous familiarity with technologies in general and good level of understanding of current technological landscape, which the younger generations are more prompt to (Xu et al., 2014), in combination with the sample specificities, did not allow us to steer the respondents in the desired direction. Despite this result, we still consider the data fruitful for analysis, since the mean of the sample on perceived technology emergence is quite high. We, thus, make a conclusion that all the respondents judged bionano technology to be emerging, which will be taken into consideration later.

3.3. Reliability and validity

Firstly, the factor analysis was conducted in SMART PLS 4. Further, the HTMT, suggested by Henseler et al. (2014), showed the ratios <0.9, which allowed us to proceed with the analysis (see the data in Figures 6-8 in Appendices).

Apart from that, construct reliability was also checked for Study 1. The variables' descriptive statistics and reliability analysis are shown in Figure 9. Unexpectedly, CBT demonstrated a poor Chronbach's Alpha of 0.55, although the AVE was above 0.5. Hence, a decision was made to eliminate the variable from further analysis, due to its poor construct reliability. The same was done for the PPA construct, which demonstrated problems with both Chronbach's Alpha and AVE. This goes in contrast with the value demonstrated in Wang et al. (2011), which may be true due to the adoption of construct items from a different research domain. Unfortunately, due to such a low result, the construct reliability was doubtful, which is why the variable was eliminated from further analysis. No issues were detected with collinearity statistics, since no VIFs > 3.3 were found, as per Sarstedt et al. (2017).

As suggested by Sarstedt et al. (2017), methods to identify model fit in PLS-SEM analysis are very limited and yet not explained in the literature well, which is why goodness of fit in such studied should be reported with caution. One of the ways to test it is the Standardized Mean Square Residual (SMSR) parameter, built in SMART PLS 4. As read in Hu and Bentler (1999), a value less than 0.1 is considered a good model fit. The SMRS of the current model was calculated to be equal to 0.06, which can be judged acceptable.

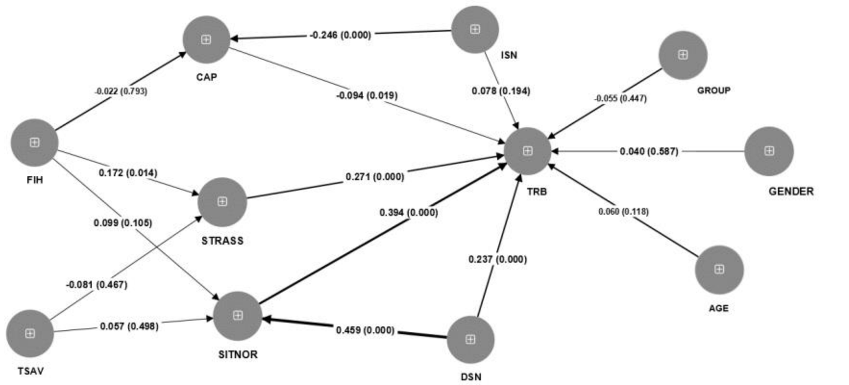
Results for Study 1

Assessment of the structural model

In order to test hypotheses H1, H2, H3, H4, H5, H6, H7, H8, H9, and H10, PLS-SEM analysis was conducted, followed by the bootstrapping procedure, as depicted in the methods description. As suggested by Hair et al. (2014), to assess a structural model, the path coefficients, the level of R^2 of constructs, and the effect size, measured by Cohen's f^2, will be taken into consideration.

Following guidelines by Sarstedt et al. (2017), the adjusted R^2 was used, since it is a more rigorous conservative approach to tackle the explained variance of endogenous variables in the model. According to the authors, the value can be interpreted as weak when it stands at around 0.25, moderate at 0.50, and substantial at 0.75. The current models R^2 are equal to 0.06, 0.23, 0.03, and 0.69, respectively, for CAP, SITNOR, STRASS, and TRB, which means the dependent variable showed a moderate degree of explanation.

Path estimates of the structural model in Study 1



Note: *p-values are displayed in the brackets after the respective path coefficients
**paths are highlighted using absolute path coefficient value strength

Figure 10 shows the results of a bootstrapping procedure, applied to the established structural model in SMART PLS 4. Path coefficients will be assessed along with the Cohen's f^2 effect size values, which measure the impact of a construct by calculating the change in the predictive variables' R^2 if the analyzed construct is omitted from analysis (Cohen, 1988). Cohen defines the effects as small, medium, and large for f^2 values of 0.02, 0.15, and 0.35, respectively.

It was impossible to test H1 and H2, due to the elimination of PPA variable from the model. Instead, it was decided to test for the direct relation between FIH and CAP, which appeared insignificant, with a path coefficient of -0.02, $p = .793$. The f^2 of the relation = 0.001, which was also low. However, the path coefficient between CAP and TRB was significant (-0.09, $p = .019$), which supports H3. The f^2 for the relation = 0.02 (small effect size by Cohen).

Commented [FA8]: It's only the p itself that is italics, not the value.

Furthermore, hypotheses related to social norms need to be looked at individually, since H4 (ISN → TRB) was rejected (path coefficient of 0.08, $p = .194$), meanwhile H5 (DSN → TRB) was supported (path coefficient of 0.24, $p < .001$). The strength for the latter effect size was medium ($f^2 = 0.14$). What is more, the relation between descriptive social norms and situational normality was also analyzed, since it had a relatively strong effect ($f^2 = 0.27$). The path estimate was significant at 0.46, $p < .001$. Therefore, if individuals perceive that others use the technology, they are likely to find it situationally adequate, and, therefore, put more trust in it. However, the direct effect was also significant, which means that DSN → TRB was only partially mediated by SITNOR. The total indirect effect of DSN on TRB equaled to 0.18, which is lower than the respective direct effect. Likewise, another relation, which appeared to be strong, and was not originally hypothesized, was measured: ISN → CAP. It turned out that CAP fully mediated the relation between injunctive social norms and trusting beliefs. The strength of the respective effects was small though ($f^2 = 0.06$ and 0.02). The total indirect effect of ISN on trust also was relatively low – 0.02.

It was not possible to assess H6 either, since the CBT construct was not reliable in Study 1. The relation between FIH and SITNOR, hypothesized in H7 turned out not significant (0.01, $p = .105$), while another relation FIH → STRASS was found relatively strong (0.17, $p = .014$; $f^2 = 0.03$). The total indirect effect of FIH on TRB stood at 0.09. At the same time, H8 is rejected, since TSAV was not predictive of either SITNOR or STRASS (see Figure 10). H9 and H10 were both supported, with quite a strong effect size of the relations. SITNOR had the biggest correlation with TRB (0.39, $p < .001$; $f^2 = 0.2$ – medium effect size by Cohen), but STRASS was also significantly predictive of trusting beliefs (0.27, $p < .001$; $f^2 = 0.12$ – small effect size). Since the manipulation did not work in the current study, it was not possible to assess the rest of the hypotheses, related to the differences between the emerging and the existing conditions.

Discussion for Study 1

Research conducted in Study 1 aimed at examining the adequacy of classic models of technology acceptance for the current circumstances and answering the research question about the presence of statistical diversity in relations between the faith and confidence predictors when tested for existing versus emerging technologies. In fact, only the first part of the objective was reached with the conducted study. It should be noted that these results are likely to be specific to emerging technologies, since the participants perceived bionano sensors as such.

Firstly, it was interesting that, in contrast to the claims by Mazey (2018), Lyons et al. (2020), and Bradford et al. (2020), individual differences, in particular, FIH and TSAV were not very important in the model. One of the possible explanations for this could be that individual differences on their own may be less significant for newer technologies. As suggested by Lyons et al. (2020) "it is possible that the role of individual differences as a predictor of trust will diminish over time as humans gain greater awareness of… [novel technologies]" (p. 4). Since the bionano sensors most likely were perceived by the sample of the study as an emerging technology, we can assume that this factor could influence such outcomes. Yet, this needs to be further analyzed under comparison of differences between emerging and existing technologies. Another reason why individual differences were not very significant could be that the population was not randomly represented in the sample: only younger people under 28 years old were recruited. According to Xu et al. (2014) and Bouwman and van de Wijngaert (2009), people of this generation are “digital natives”, meaning that they have enough experience with technology in general and find its usage normal, regardless of the personal characteristics.

As predicted, STRASS and SITNOR were strongly correlated with TRB. It is important to underline that the strength of the relation was larger for the faith predictor – situational normality – that goes in line with Bodo (2020). Furthermore, CAP was also significantly related to trust, which corresponds to the results by Mazey (2018), Li et al. (2008), and others. Apart from that, the CBT variable was excluded from analysis, which is why its influence on trusting beliefs could not be measured within Study 1.

Finally, slightly unexpected results were obtained regarding the social norms. Only the DSN had a direct effect on trust – the ISN did not, which proves the assumption that these variables should be studied in separation. The ISN’s effect on TRB was fully mediated by CAP, meaning that people who suppose that significant others would approve of their technology usage are less concerned about their private data. Potentially, this effect could be explained by the consumer conformity, which suggests that trust and usage intentions of a technology in the 21st century are dependent on social ties, strategic complements, and image related issues, which make users less prompt to raising concerns about their privacy (Princes et al., 2020). All these factors are directly connected to the essence of the injunctive social norms. Additionally, the mediating effect on trust, as opposed to the direct effect, could be obtained because ISN directly predicts the willingness to use a technology, as underlined by King and He (2006), rather than the trust itself. Apart from that, DSN strongly predicted SITNOR, which naturally makes sense, since the perception of adequacy of a certain situation is strongly influenced by other individuals’ behaviours, through the effect on people’s subjective perceptions of norms (Liu & Shi, 2018).

Limitations for Study 1

Despite interesting results, the current study has some limitations as to its design and reliability, so to its generalization potential. Firstly, due to time and resources limitations, the study was built in one questionnaire, which gathered data on all variables at one point in time, thus, making research prompt to common method bias. Although question randomization, attention and manipulation checks, and the conducted discriminant validity analysis (Kock, 2015) suggest that it is not likely to be an issue in the current study, it may have still impacted slightly the outcomes of the research. Furthermore, perceived power asymmetry and calculus-based trust's reliability was not established, which is why the model was tested without the constructs. Another potential limitation lies in the fact that the questions used self-reported data, which, however, does not annul the significance of the results (Hair et al., 2014). In terms of generalization potential and external validity, although several variables were controlled for and the sample size does not seem to be a problem (Kock & Hadaya, 2016; Wilson Van Voorhis & Morgan, 2007), other factors, such as cultural differences could also interfere with the results, which calls for future cross-cultural analysis. Furthermore, a sample of students was employed, which limited the age of participants to the range between 20 and 28 years. This did not allow testing for potential differences between model path estimates for younger and older people, which could have an impact on the study's external validity.

Apart from that, the quantitative nature of the study on its own may bring a limitation (Mazey, 2018). The nature of such a complex phenomenon as trust is intangible, and a positivistic view of the ability to assess every person's behaviour on the basis of one single system of goals and priorities may turn out impossible in real life scenarios. The research, thus, seeks to simplify the situation to a volitional decision of a person who is not demanded by anything or anyone to use a specific technology, which may overlook important socio-economic factors. Experimental design also tends to limit studies' external validity, although it may not be of such importance for PLS-SEM analysis, according to Hair et al. (2017).

Furthermore, while conducting Study 1, we tried to be experimentally rigorous to additionally ensure the external validity of the results. However, this approach failed to elicit sufficient difference in "emergence" perception between groups. Therefore, further investigation, based on the comparison between distinct technologies (one emerging and one non-emerging) is proposed. The study was also limited to looking in trusting technology beliefs alone, without testing for further processes of transforming these beliefs into specific actions, such as technology usage or at least intentions of such (e.g. according to the Reasoned Action Theory by Fishbein & Ajzen [1975], which was used in prior research – see McKnight et al. [2014]). This was done on purpose in a pay-off between making the model as complete as possible and collecting enough reliable responses from participants.

Yet, further studies should account for such potential model extensions, and, especially, for if and how initial technology trust flows into continuous technology usage.

Commented [FA9]: I think you should end with the limitation that by trying to be experimentally rigorous it did not elicit different perceptions of "emergingness". That then fits really well with introducing study 2.

Commented [FA10]: I would leave this "limitation" to the end of the paper, the discussion. This is not really a limitation, it's just a matter of focus. And it would make sense to add questions on this to the next study if you thought about it now 😉 so I suggest just saying it at the end.

Methodology and data collection for Study 2

Following the results obtained in Study 1 and taking into consideration its limitations, it was decided to attempt to reassess the hypotheses under a slightly different context. The general methodology of Study 2 was identical to that of Study 1, which is why only the differences between the two will be looked at in this chapter. The major limitation that we tried to address in Study 2 was the failed manipulation. Another pre-test was added to Study 2 to avoid the same problems as Study 1 had. Furthermore, a less rigid study with two distinct technologies – bionano sensors and smartphones – was developed. In addition to bionano technology, smartphone technology was chosen as a currently popular, commercialized product that the majority of people is familiar with and uses on a daily basis (existing technology). By categorization conducted in literature (Mazey, 2018), it was proven to belong to existing technologies, which was tested using Tukey post-hoc analysis. Belonging to this group was identified through consecutive rejection of emerging technology framework criteria matching. In order to recreate the experimental manipulation of emerging/existing conditions, a change in the treatments was made.

Treatments

In order to manipulate the degree of emergence of the technology, the treatments were altered. The scripts were edited to present bionano sensors either as an emerging technology and smartphones as an existing one. Like in Study 1, the scripts were written as close to each other as possible between conditions. Further, the videos were changed as well to match the new scripts (see Figures 11-12 in Appendices).

Pre-tests

Because of the use of distinct technologies in Study 2, firstly, the neutrality of the videos was assessed by conducting a between-subject pilot test on a non-probability convenience sample (N = 20). The subjects were randomly presented with either the smartphone or the bionano video in a web-based questionnaire built in Qualtrics software, after which a set of questions was asked on their emotions right after they watched it. These included 1-7 Likert-scale items "How much information did this video provide?" (1 = Very little; 7 = Very much), "How strong and emotionally saturating was the text of the video?" and "How strong and emotionally saturating were the images of the video?" (1 = Not at all;

7 = Totally). They were followed by the PANAS scale questions on positive/negative emotional affects (Watson et al., 1988).

The data was analyzed in Microsoft Excel, using independent sample *t*-tests. The 9 people in the smartphone group ($M = 2.4$, $SD = 0.8$) and the 11 people in the bionano group ($M = 1.9$, $SD = 0.5$) demonstrated no significant differences on the PANAS positive affect, $t(18) = 0.49$, $p = .15$. Lack of significant differences between the groups with smartphone ($M = 1.7$, $SD = 0.3$) and bionano ($M = 1.5$, $SD = 0.5$) conditions was also obtained on PANAS negative affect, $t(18) = 0.18$, $p = .36$. Similarly, results on other questions showed no significance at a confidence level of 95%, meaning that the videos were unlikely to cause varying effects on participants between conditions and draw them towards particular responses, reassuring better internal validity. The full data set is available online here.

Instruments

Mostly, the same instruments as for Study 1 were used for the replication**.** Furthermore, particular distinctions were made in regard to the differences between the emerging and the existing conditions, following the "Faith-Confidence" logic by Bodo (2020). The list of hypotheses for Study 2 is, therefore, identical to Study 1.

Apart from this, we also attempted to resolve the issue with the PPA variable scale that had demonstrated poor Chronbach's Alpha in the first experiment. To do that, a new scale by Wang et al. (2011) was adopted for the construct measurement.

Sample and data collection

A total of 400 cases were gathered for Study 2, using Prolific platform for data collection. It was a convenience non-probabilistic sample, since the participants were not recruited from the population randomly. Instead, all English-speaking Prolific users of 18 years of age or older were called to take the questionnaire. All of the 400 participants received a post-survey monetary incentive of 0.78£, which ensured that there was no missing data. The data quality was additionally increased by allowing survey completion only via desktop and not via mobile devices. Nonetheless, 22 responses were excluded from the study due to failed attention or manipulation checks, which resulted in 378 unique cases in the final data set. As mentioned earlier, the required amount of participants to ensure the desired statistical power of PLS-SEM analysis stands at 155 cases (Kock & Hadaya, 2016), which makes the given sample size adequate for the research objectives.

The study had participants from 21 countries, including the Great Britain (58.9%), Canada (18.8%), the USA (7.8%), Australia (5.9%), New Zealand (1.9%), and others. 51% of the respondents were male and 49% female, the non-binary/other genders were not present in the sample. Participants' age varied from 18 to 60 years old (M = 34.5, SD = 10.2).

Manipulation validity

Study 2 followed identical data analysis procedures to Study 1. Therefore, the data was assessed for manipulation validity first, as suggested by Straub & Gefen (2004). Apart from the attention and manipulation checks, the study's treatment conditions were analyzed for heterogeneity, using independent sample t-test. In contrast to Study 1, where the manipulation did not work, the mean difference between the smartphone technology (M = 3.58, SD = 1.78) and the bionano technology (M = 5.14, SD = 1.7) was significant, $t(376)$ = -8.96, $p < .001$, with the latter one being perceived as a more emerging technology. The mean for bionano condition is comparable to the one obtained earlier in Study 1 (M = 5.31, SD = 1.15), which proves that our assumption of the reasons for failed manipulation in Study 1 were probably right.

Due to the passed test on groups heterogeneity, we managed to proceed to the multi-group analysis using PLSPM method, which was carried out in SMART PLS 4. The data was subdivided into several groups: comparisons were made between the emerging/existing technology and age differences. Following the guidelines by Cheah et al. (2020), to safeguard the validity of the results, measurement invariance of composite models (MICOM) procedure was performed, where partial measurement invariance was established on the basis of compositional invariance and configural invariance, which allowed us to carry out the Henseler's bootstrap-based MGA (Henseler et al., 2009).

Validity and reliability

As mentioned earlier, in order to ensure construct reliability, firstly, the factor analysis was conducted. Figure presents the factor cross-loadings obtained in SMART PLS 4 for the research model. Apart from that, according to the heterotrait-monotrait ratio of correlations (HTMT), run in SMART PLS 4, as guided by Henseler et al. (2014), the ratios for all constructs were below 0.9, which shows that the discriminant validity was established. See the data in Figures 13-15 in Appendices.

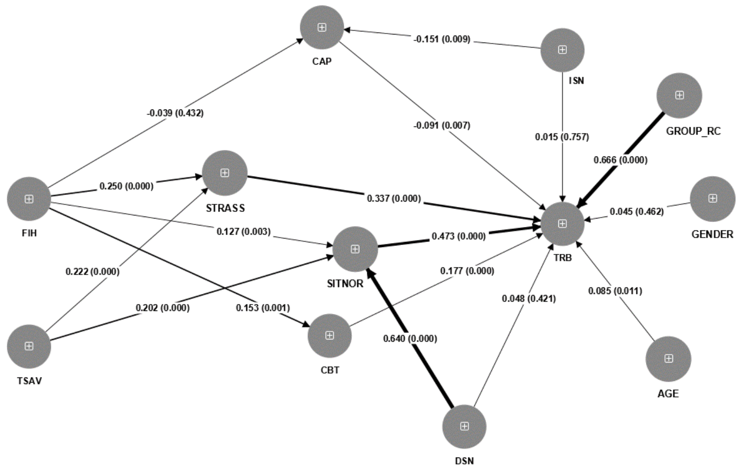
Furthermore, in accordance with PLS-SEM recommendations, construct reliability was further checked, using Chronbach's Alphas. The variables descriptive statistics and reliability analysis can be found in Figure 16**.** As seen from the table, although all constructs demonstrated satisfactory AVE, perceived power asymmetry construct showed a poor Chronbach's Alpha again, despite being adopted from prior research. Unfortunately, within the scope of the current paper we did not manage to find an appropriate scale for perceived power asymmetry, since two distinct measurements, adopted from other research fields, failed to demonstrate reliability in technology acceptance area. Apart from that, three constructs demonstrated Chronbach's Alphas close to 0.7 – 0.69, 0.69, and 0.67 for concern about privacy, calculus-based trust, and descriptive social norms, respectively – which is adequate for exploratory research, as depicted in Nunally & Bernstein (1994). Collinearity analysis was also conducted, with no VIF > 3.3, which is deemed appropriate, as per Hair et al. (2017). Following the same procedures as in Study 1, the SMRS of the model was measured in SMART PLS 4. The SMRS of the current model was calculated to be equal to 0.06, which is a good model fit, as per Hu and Bentler (1999).

Results for Study 2

Assessment of the structural model

The data analysis also followed the same procedure as for Study 1. The adjusted R^2 of the current model's variables generated as follows: 0.02, 0.05, 0.5, 0.09, 0.65 for CAP, CBT, SITNOR, STRASS, and TRB, respectively. This means that all the variables' values can be assessed as weak, except for the major DV – TRB – and SITNOR, which showed moderate R^2.

Path estimates of the structural model in Study 2



Note: *p-values are displayed in the brackets after the respective path coefficients
**paths are highlighted using absolute path coefficient value strength

The Figure “*Path estimates of the structural model in Study 2”* shows the path coefficients and the associated p-values obtained for the structural model relations. Testing for H1 and H2 was again not possible, since the PPA construct demonstrated poor reliability (see section 7.6) and was eliminated from the final model. Instead, a direct relation between FIH and CAP was tested, which appeared to not be significant at a path coefficient of -0.04, p = .432. Similarly, f^2 of the relation equaled to 0.002, which represents a very low value. In contrast, H3 is supported, since there is a significant negative relation between CAP and TRB (path coefficient of -0.09, p = .007), f^2 = 0.02 (small effect size). It suggests that concern about privacy explains 1.9% of the variance of trusting beliefs in technology, so that higher CAP leads to lower TRB.

Further, H4 is rejected, since ISN was not significantly predictive of TRB (path coefficient of -0.02, p = .757; f^2 < 0.001). Instead, it turned out that CAP fully mediates the relation between ISN and TRB: path coefficient between ISN and CAP equals to -0.12, p = .009, and f^2 of 0.02 (small effect size). It suggests that the more individuals think that their significant others would recommend them or expect them to use a technology, the less concern about privacy they demonstrate towards this technology. In turn, lower CAP results in higher trusting beliefs. The indirect effect of ISN on TRB is quite little though (0.01). This completely replicates the respective results of Study 1. On the other hand, H5, which considers the relation between descriptive social norms and technology trusting beliefs, is rejected: the direct relation showed a path coefficient of 0.05, p = .421, and f^2 of 0.002. However, when testing the model, it was gathered that DSN had a very strong predictive relation with SITNOR, with a path coefficient of 0.64, p < 0.001, and f^2 = 0.81 (large effect size). This result suggests that the influence of DSN on the TRB is fully mediated by SITNOR, with a large indirect effect of 0.3.

Following the hypotheses testing further, H6 is supported, with a 0.18 path coefficient, p < .001, and the f^2 of 0.07 (small effect size). In the same manner, H7 is supported, with the path coefficient of 0.13, $p = .003$, and f^2 of 0.03, for the relation between FIH with SITNOR. What is more, although not hypothesized, the relation between FIH and STRASS was also deemed significant (path coefficient of 0.25, $p < .001$; f^2 of 0.07). The total indirect effect of FIH on trust accounted for 0.19. Apart from that, H8 is supported due to a strong path coefficient between TSAV and SITNOR (0.2, $p < .001$; f^2 of 0.08). Similarly, although not initially hypothesized, TSAV was also slightly but significantly predictive of STRAS (0.22, p < .001; f^2 of 0.03). The TSAV’s total indirect effect on TRB, therefore, equaled to 0.15.

Likewise, H9 and H10 uphold due to significant path coefficients between SITNOR and TRB (0.47 at $p < .001$; $f^2 = 0.13$ – medium effect size) and STRASS and TRB (0.34 at $p < .001$; $f^2 = 0.09$ – small effect size). Furthermore, while one of the control variables that were assessed in relation to the DV – gender – was not found significantly predictive of TRB, the other one – age – generated a significant result, which will be further evaluated at the next step along with the MGA for the emerging/existing group differences.

Multigroup analysis results

In order to test for the remaining hypotheses, specific to differences between existing and emerging technologies, as well as for the significantly impacting the DV control variable – age, a MGA was further conducted based on the process description in section 7.5. It was run on 5000 bootstrap replications with a 95% confidence interval, as suggested by Harborth & Pape (2017). Figures 17-18 in Appendices highlight paths coefficients for the structural model obtained under existing and emerging technology conditions individually. Figures 19-20 in Appendices represent bootstrapping results for those individual paths coefficients between conditions and the respective bias-corrected confidence intervals.

Path coefficients comparison between conditions (PLS MGA result) in Study 2

Test	Bootstrap MGA			Parametric test			Welch-Satterthwait test		
Test Stat. / Relations	Difference in path coefficients	1-tailed p-value	2-tailed p-value	Difference in path coefficients	t-value	p-value	Difference in path coefficients	t-value	p-value
AGE ➤ TRB	.039	.274	.547	.039	0.598	.550	.039	0.599	.550
CAP ➤ TRB	-.055	.792	.417	-.055	0.811	.418	-.055	0.811	.418
CBT ➤ TRB	.152	.015	.031	.152	2.159	.031	.152	2.166	.032
DSN ➤ SITNOR	-.175	.975	.051	-.175	1.946	.052	-.175	1.948	.053
DSN ➤ TRB	-.107	.897	.206	-.107	1.277	.202	-.107	1.281	.202
FIH ➤ CAP	-.217	.987	.027	-.217	2.240	.026	-.217	2.242	.026
FIH ➤ CBT	.086	.216	.432	.086	0.787	.432	.086	0.786	.433
FIH ➤ SITNOR	.314	.001	.001	.314	3.262	.001	.314	3.268	.001
FIH ➤ STRASS	.193	.043	.085	.193	1.746	.082	.193	1.748	.082
GENDER ➤ TRB	-.170	.919	.162	-.170	1.402	.162	-.170	1.404	.162
ISN ➤ CAP	.329	.007	.015	.329	2.410	.016	.329	2.418	.017
ISN ➤ TRB	.013	.438	.876	.013	0.162	.871	.013	0.162	.871
SITNOR ➤ TRB	-.400	.999	.002	-.400	3.290	.001	-.400	3.284	.001
STRASS ➤ TRB	.363	.001	.002	.363	3.133	.002	.363	3.126	.002
TSAV ➤ SITNOR	.151	.038	.077	.151	1.751	.081	.151	1.754	.081
TSAV ➤ STRASS	-.034	.643	.715	-.034	0.360	.719	-.034	0.360	.719

Note: significant differences are highlighted in grey

According to the differences between conditions seen in the model paths coefficients, some interesting results were found regarding the FIH → CAP relation, where for the existing technology condition (-.17, $p = .013$) it was significant, while for the emerging one (0.04, $p = .541$) it was not. This difference is substantial, according to the parametric test. Although this finding is fruitful, the absence of the PPA variable, which had to be eliminated from the model, does not let us test for hypotheses H1a and H2a.

Apart from that, other paths, which were not originally hypothesized, generated interesting MGA results: for instance, AGE → TRB, where the path coefficient was significant for the smartphone group (0.1, p = .*045*), and not significant for bionano group (0.06, p = .*178*). However, the magnitude of this variety, according to the bootstrap MGA procedures, displayed in Table 14, was not enough to report significant differences. In the same way, the individual path coefficient for the relation between CAP and TRB was significant for the existing technology group (-0.11, p = .*021*), and not significant for the emerging technology group (-0.06, p = .*257*), yet, not generating significant differences in the parametric test, therefore, H3a is rejected. Furthermore, hypotheses H4a and H5a are not supported either, since ISN → TRB and DSN → TRB did not demonstrate significant differences between conditions. On the other hand, since we identified earlier that the influence of ISN on TRB is fully mediated by CAP, it is fruitful to underline that the relation of ISN on CAP showed significant paths' differences between conditions. It almost does not affect concern about privacy for smartphone users (0.01, p = .*937*), while for bionano group higher ISN leads to significantly lower CAP (-0.32, p < .*001*).

H6a is supported, with parametric test difference between groups' paths coefficients of 0.15, p = .*031*. The magnitude of CBT influence on TRB is, therefore, significantly bigger for the original data set for existing technology condition (0.25, p < .*001*) in comparison to the emerging one (0.1, p = .*025*). The same holds for the differences between FIH and SITNOR relation, with even bigger gap between path coefficients of smartphone group (0.35, p < .*001*) and bionano group (0.04, p = .*545*), thus, supporting hypothesis H7a. In contrast to this, H8a is rejected, since the influence of TSAV on SITNOR was not significantly different between conditions (path coefficients difference of 0.15, p = .*077*).

Finally, hypotheses H9a and H10a are both supported, with the significant differences between treatment groups. For the relation of STRASS and TRB, as expected, the effect is quite large for the existing technology (0.45, p < .001), and not significantly present for the emerging one (0.09, p = .339). In contrast, SITNOR, which was referred to as one of the faith predictors, has a stronger influence on TRB for the bionano group (0.64, p < .001) than for the smartphone group (0.24, p = .*02*).

Further, a MGA was conducted with the same parameters to test for moderation of age. For that purpose, data set groups were generated, with group 1 including people of 34 years old or younger (which was a mean of the sample) and group 2 with participants of 34+ years of age. Figure 21 in Appendices shows the results of this analysis, where the only significant difference between age groups was TSAV → SITNOR (-.15, p = .046), with younger people demonstrating higher SITNOR at lower values of TSAV in comparison to older ones. At the same time, with stronger TSAV, the difference is almost leveled out (see simple slope analysis of moderation in Figure 22, Appendices).

Discussion for Study 2

Research conducted in Study 2 aimed at tackling the issues with the manipulation validity in Study 1 in order to test for the presence of statistical diversity in relations between the faith and confidence predictors when tested for existing versus emerging technologies. The results presented above suggest that there is a big difference between smartphone and bionano groups, which supports claims of McKnight et al. (2014) and Mazey (2018).

As seen from Figure 23 in Appendices, when dividing factors between faith and confidence groups, it appears that the significant differences indeed suggest that emerging technologies are more dependent on some of the faith constructs, which demonstrate stronger predictive power over confidence ones (e.g., situational normality and injunctive social norms). As suggested in the literature review, this is likely to happen due to a lower initial familiarity with the technology, less protection by institutional bodies, and the consequent complicated process of rational assessment of the situation. It goes in line with suggestions by Bodo (2020), Li et al. (2008), Mazey (2018), and others.

On the other hand, several confidence predictors seem to be more impactful when addressing an existing technology rather than an emerging one (e.g. structural assurance and calculus-based trust). Both constructs are based on the rational assessment of available information about the technology. This result supports prior evidence by Beldad and Henger (2017), Bodo (2020), Garry & Harwood (2019), and others.

Figure 24 in Appendices highlights support of all the hypotheses and additional observations for both studies. It was impossible to assess the perceived power asymmetry variable, due to an insufficient construct reliability. However, faith in humanity, which was directly connected to concern about privacy in the absence of PPA variable, turned out to have a significantly stronger effect for the existing condition, rather than emerging, which could potentially mean that PPA might belong to the confidence predictors, as opposed to the faith ones. However, the mere significance for the model and the above-given assumption both need to be further assessed and tested with a different PPA scale, applied to technological domain specifically. However, another explanation for this result could be simply that individual differences may be less significant for emerging technologies in general, as suggested by Lyons et al. (2020). This claim would support the observations made in Study 1 of FIH and TSAV being less significant for the model.

Concern about privacy was influential on trusting technology beliefs equally for both conditions, which may be a result of a specific choice of technologies, since both smartphone and bionano technology usage requires extensive data collection and may be potentially dangerous for end-users in terms of personal data leakage (Xu et al., 2014), which most users are aware of. Apart from that, social norms, either injunctive or descriptive, were not directly predictive of trusting beliefs. On the other hand, some interesting results were obtained when testing for mediating relations: e.g., it turned out that concern about privacy fully mediates the relation between ISN and TRB, suggesting that reliance on prediction of significant others to recommend technology usage mitigates the effects of privacy concerns when applied to novel scenarios. However, the indirect effect of ISN on TRB is quite low, just like in Study 1, which, once again, steers us to believe that assumptions by King and He (2006) that ISN directly predicts usage as opposed to trust might be true.

Furthermore, in Study 1 DSN directly influenced TRB in the structural model, which was not replicated in Study 2. Potentially, this could have happened due to fact that descriptive social norms are more influential on trust for emerging technologies rather than existing ones (the difference between groups in Study 2 is also almost significant on this relation for the bionano condition). At the same time, when structural assurances and familiarity with the technology are in place, social norms in general become less important. Similarly, descriptive social norms, in particular, generated to be predictive of situational normality, through which they demonstrate full mediating effect on TRB for the existing technology and partial mediation for the emerging one. The same outcomes were obtained in Study 1 for the mediating effects. Such results correspond to claims by Lie t al. (2008) and Bouwman and Wijngaert (2009), which show that social norms oftentimes appear significant only when studied in separation from TAM or similar models, since the power of their direct relation on trust is relatively low. It may be fruitful to examine if DSN could belong to the faith predictors group, as opposed to the expected confidence group, since the perception of the number of people using a technology or recommending it may not be objective and rational, but subjective and driven by emotional assessment (Anderson et al, 2011). However, this opinion is opposed to Mazey's (2018), who highlights that "individuals with more knowledge about a technology are more likely to perceive it as being desirable by society" (p.95), and therefore, the nature of this relation should be further tested.

Although expected to only have influenced situational normality, technological savviness and faith in humanity were both predictive of structural assurance as well. It goes against findings by Li et al. (2008). Study 1 also did not demonstrate significant relations between TSAV and other variables, nor the FIH's influence on SITNOR. However, McKnight et al. (2014) theorized SITNOR and STRASS as parts of a second-order construct – institutional-based trust – and the results of the current analysis showed that the two cross-loaded on each other slightly, which is why it is not surprising to see such relations. Lyons et al. (2020) and Mazey (2018) also suggest that faith in humanity is predictive of IBT as a whole, and, consequently, of both of its parts in separation too.

Finally, as predicted, situational normality appeared to be more significant in relation to emerging technology trusting beliefs in comparison to the existing one, in contrast to structural assurance, which demonstrated the opposite result. This underlines the importance of separation of the two constructs and their individual assessment as opposed to a single variable of institution-based trust, initially proposed by McKnight et al. (2014). Their model was adopted from people-to-people trust research, which suggested that individuals increase their reliance on both STRASS and SITNOR in ambiguous novel situations. Yet, it bases on the preliminary presence of established laws and regulations in regards to the applied situation, meanwhile, disruptive technologies tend to alter business-models, and, thus, proper regulations are currently not established in technological domain, which may explain this difference.

Limitations for Study 2

In general, it appears that the model relations are relatively stable between experiments, although some limitations, including the sample choices and failed manipulation check in Study 1 did not let us fully compare all the results between studies. The list of limitations for Study 2 includes the same issues as Study 1, namely, slight probability of common method bias questions, self-reported questions, lack of control for certain socio-economic factors, a positivistic view on trust assessment, experimental quantitative design, and lack of model extension that would account for the actual system usage. On the other hand, Study 2 tackled very significant issues of manipulation validity and young sample, and, therefore, allowed for testing of the main research question.

In turn, this created another limitation (which, however, proved to be necessary): some of the results seem to be specific to the particular technologies that were chosen for the current analysis. As per Mazey (2018), McKnight et al. (2014), Li et al. (2008), Lyons et al. (2020), Garry and Harwood (2019), and many other authors, trust in technology is very context- and time-specific, which is why constant reassessment of existing models is necessary, and the difference between types of technologies can be vast.

Conclusions and future research directions

Commented [FA11]: I think you could try and propose how to tackle the issue we had with manipulating the perception of emerging technology, if you can think of sth. And say future studies should replicate your model with both higher internal and external validity. A potential way could be...

It is expected that the findings of the two studies will highlight to academics and practitioners that trust in technology is, indeed, a very dynamic and context-related factor. However, with all the complexity of this construct, it proves to still be a matter of vast significance for the economic and social development of the communities, countries, and the world altogether. The current research shed a light on the changing structural relations between classic variables, studied within the technology acceptance domain, with empirical support. Given the interest of the governments and private entities in increasing the digitalization potential, we come back to the quote by Y.N.Harari: “In the early twenty-first century, the train of progress is again pulling out of the station. Those who miss this train will never get a second chance” (p.77). The results of this exploratory analysis may be instrumental in providing empirical proof of the theory of “Faith-Confidence” predictors by Bodo (2020), which is a novel contribution to the literature. In general, the PLS-SEM analysis showed that two distinct cognitive processes function for emerging and non-emerging technologies. In particular, the findings that such variables as situational normality and injunctive social norms seem to be more predictive of emerging technologies could be invaluable for future research and application of TAM and other models’ extensions.

A comprehensive integrative structural model of technology trusting beliefs, assessed in this exploratory paper, provides a solid foothold for further research on trust antecedents in the disruptive and fast-paced environment of the Industry 4.0. Future studies should replicate this model on other types of technologies. What is more, a cross-cultural analysis might be fruitful in order to assess the possibility of differences to the model between nations.

The unique contributions of the current studies include the development of a new technology trust antecedent “perceived power asymmetry”. However, two attempts of application of existing PPA scales from other research areas did not generate reliable results for technological context, which is why a separate study for measurement scale development could be beneficial in the future. Apart from that, a new individual difference was drawn – technological savviness – which reached significance in technological acceptance, especially, for older generations. It is important to note that the effects of individual differences seem to be diminishing for younger generations and newer technologies. Further investigation of their relations to trust in technology can be vital for the changing societal dynamics. Similarly, it was crucial that the subjective norms were divided into descriptive and injunctive ones, which had never been done before in technology acceptance research. This proved to be valuable, since distinctive variety was demonstrated by these constructs. Likewise, the division between situational normality and structural assurance from the single institutional-based trust variable was influential in identifying the differences between existing and emerging technologies.

However, the current studies were limited to looking in trusting technology beliefs alone, without testing for further processes of transforming these beliefs into specific actions, such as technology usage or at least intentions of such (e.g. according to the Reasoned Action Theory by Fishbein & Ajzen [1975], which was used in prior research – see McKnight et al. [2014]). This was done on purpose in a pay-off between making the model as complete as possible and collecting enough reliable responses from participants. Yet, further studies should account for such potential model extensions, and, especially, for if and how initial technology trust flows into continuous technology usage.

Commented [FA12]: I think you should end with the limitation that by trying to be experimentally rigorous it did not elicit different perceptions of "emergingness". That then fits really well with introducing study 2.

Commented [FA13]: I would leave this "limitation" to the end of the paper, the discussion. This is not really a limitation, it's just a matter of focus. And it would make sense to add questions on this to the next study if you thought about it now 😊 so I suggest just saying it at the end.

Additionally, future studies should replicate the model with both higher internal and external validity. One of the ways to do this could be finding a technology that people would be less likely to be aware of, and manipulating the perception of its emergence. It is possible that a more detailed information on the technological properties, applications, and potential privacy risks could help steer participants to believe the technology to be either emerging or existing.

In conclusion, trust in technology as a crucial part of social trust is becoming ever more important for technology vendors, medical companies, and governmental entities. Multiple devices that are embedded in our everyday lives shape the way we interact, work, and make decisions. In general, the current approach to technology trust in the literature, which treats all the types of technologies similarly, without a distinction between their properties, seems to be outdated, since the disruptive Industry 4.0. is bringing new factors into play. It appears that if companies and governments introduce new technologies, following old rules and principles and expecting the same consumer response, they might face challenges with technology acceptance from the public.

Understanding the observed difference in the overall perception and the specific trusting antecedents between emerging and existing technologies could, therefore, be key in successful communication with the general population. The consequences of the crisis of trust, which is affecting many economic spheres, can be mitigated by transparent and properly regulated business activities and governmental interventions. In particular, if the introduction of novel technologies is expected, such interventions should specifically target the "faith" predictors of technology trusting beliefs and ensure the credibility and security of personal data usage. When the technology is more familiar to the general public, structural assurances and other "confidence" predictors should be targeted instead. Future research in public policy domain should concentrate on investigating the ways to best communicate these messages.

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Appendices

Figure 1

Criteria for technological degree of emergence, retrieved from Mazey (2018)

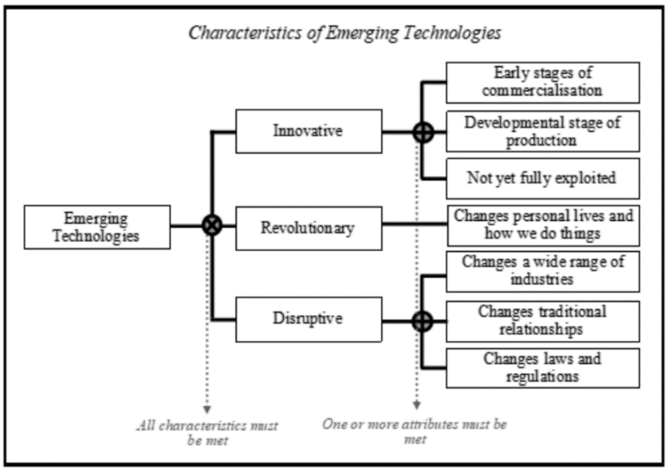


Figure 2

List of research questions and hypotheses

RQ 1: Is there a significant statistical difference in relations between the model variables, and, in particular, between the faith and confidence predictors, and their effects on the trusting beliefs when analyzing the existing/emerging technologies?

H1: There is a significant negative relation between faith in humanity and perceived power asymmetry

H1a: The strength of the relation is significantly bigger for the emerging technology than for the existing one

H2: There is a significant positive relation between perceived power asymmetry and concern about privacy

H2a: The strength of the relation between perceived power asymmetry and concern about privacy is significantly bigger for the emerging technology in comparison to the existing one

H3: There is a significant negative relation between concern about privacy and trusting beliefs in technology

H3a: The strength of the relation between concern about privacy and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

H4: There is a significant positive relation between injunctive social norms and trusting beliefs in technology

H4a: The strength of the relation between injunctive social norms and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

H5: There is a significant positive relation between descriptive social norms and trusting beliefs in technology

H5a: The strength of the relation between descriptive social norms and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

H6: There is a significant positive relation between calculus-based trust and trusting beliefs in technology

H6a: The strength of the relation between calculus-based trust and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

H7: There is a significant positive relation between faith in humanity and situational normality (applied to technology)

H7a: The strength of the relation between faith in humanity and situational normality (applied to technology) is significantly bigger for the emerging technology in comparison to the existing one

H8: There is a significant positive relation between technological savviness and situational normality (applied to technology)

H8a: The strength of the relation between tech-savviness and situational normality (applied to technology) is significantly bigger for the existing technology in comparison to the emerging one

H9: There is a significant positive relation between structural assurance (applied to technology) and trusting beliefs in technology

H9a: The strength of the relation between structural assurance and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one

H10: There is a significant positive relation between situational normality (applied to technology) and trusting beliefs in technology

H10a: The strength of the relation between situational normality and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one

Figure 3

Constructs' operationalization and their reliability characteristics in prior research

Variable	Definition	Scale	Adopted from
		Individual differences (IV)	
1. Faith in humanity	Belief that others are typically well-meaning and reliable	1 to 7 Likert scale from Strongly disagree to Strongly agree: Faith in **benevolence**: FIHB1 In general, people really do care about the well-being of others * FIHB2 The typical person is sincerely concerned about the problems of others * FIHB3 Most of the time, people care enough to try to be helpful, rather than just looking out for themselves * Faith in **competence**: FIHC1 I believe that most professional people do a very good job at their work * FIHC2 Most professionals are very knowledgeable in their chosen field * FIHC3 A large majority of professional people is competent in their area of expertise * Faith in **integrity**: FIHI1 In general, most folks keep their promises * FIHI2 I think people generally try to back up their words with their actions * FIHI3 Most people are honest in their dealings with others	Li et al. 2008; Chronbach's Alphas, respectively, for the three faith beliefs - 0.87, 0.88, 0.82
2. Technological savviness	Individual characteristic of a person that shows he/she is informed about or proficient in the use of modern technology	1 to 7 Likert scale from Strongly disagree to Strongly agree: TSAV1 Other people come to you for advice on new technologies * TSAV2 It seems your friends are learning more about the newest technologies than you are [reverse coded]* TSAV3 In general, you are among the first in your circle of friends to acquire new technology when it appears * TSAV4 You can usually figure out new high-tech products and services without help from others * TSAV5 You keep up with the latest technological developments in your areas of interest * TSAV6 You enjoy the challenge of figuring out high-tech gadgets. TSAV7 You find you have fewer problems than other people in making technology work for you. TSAV8 You have avoided trying new high-tech things because of the time it takes to learn them [reverse coded] * TSAV 9 You are always open to learning about new and different technologies * TSAV10 There is no sense trying out new high-tech	Parasuraman, 2000; Cronbach's Alpha = 0.8

		products when what you have already is working fine [reverse coded]	

Confidence predictors			
1. Structural assurance	Belief that success with the specific technology is likely because, regardless of the characteristics of the specific technology, one believes structural conditions like guarantees, contracts, support, or other safeguards exist in the general type of technology that make success likely	1 to 7 Likert scale from Strongly disagree to Strongly agree: STRASS1 Favourable-to-consumer legal statutes and processes make me feel secure in using [TECHNOLOGY] * STRASS2 I feel okay using [TECHNOLOGY] because they are backed by vendor protections * STRASS3 I believe effective product guarantees exist that make it feel all right to use [TECHNOLOGY]	McKnight et al., 2011; Mazey, 2018; Chronbach's Alpha = 0.83
2. Situational normality	Belief that success with the specific technology is likely because one feels comfortable when one uses the general type of technology of which a specific technology may be an instance	1 to 7 Likert scale from Strongly disagree to Strongly agree: SITNOR1 I am totally comfortable working with [TECHNOLOGY] * SITNOR2 I feel very good about how things go when I use [TECHNOLOGY]* SITNOR3 I always feel confident that the right things will happen when I use[TECHNOLOGY]* SITNOR4 It appears that things will be fine when I utilize [TECHNOLOGY]*	McKnight et al., 2011; Mazey, 2018; Chronbach's Alpha = 0.81

3. Descriptive social norms	Subjective belief about people in society that a person considers important, and his/her desire desire to use a certain technology or reject using it according to his/her knowledge of if those people are using the technology	1 to 7 Likert scale from Strongly disagree to Strongly agree: DSN1 The [TECHNOLOGY] is currently used by a lot of people * DSN2 Most users of the [TECHNOLOGY] recommend its usage * DSN3 Most users of the [TECHNOLOGY] provide their personal information to the [TECHNOLOGY]	Beldad & Henger, 2018; Cronbach's Alpha = 0.86
4. Calculus-based trust	Acceptance of a certain level of vulnerability based on the calculated costs of maintaining or severing a relationship	1 to 7 Likert scale from Strongly disagree to Strongly agree: CBT1 The [TECHNOLOGY], as well as the related government agents, has nothing to gain by not caring about me * CBT2 The [TECHNOLOGY], as well as the related government agents, has nothing to gain by being dishonest in its interactions with me	Li et al., 2008; Cronbach's Alpha = 0.82
		Faith predictors	
1. Injunctive social norms	Normative belief about people in society that a person considers important, and his/her desire to use a certain technology or reject using it according to others' expectations about how they should act and behave	1 to 7 Likert scale from Strongly disagree to Strongly agree: ISN1 I believe that most people who are important to me will think I should support the [TECHNOLOGY] * ISN2 I believe that most people who are important to me will think I should provide personal information to the [TECHNOLOGY] * ISN3 I believe that most people who are important to me will think I should use the [TECHNOLOGY]	Li et al., 2008; Cronbach's Alpha = 0.96

3. Perceived power asymmetry	Belief that the person is unable to control or negotiate the rules and conditions of technology usage	1 to 7 Likert scale from Strongly disagree to Strongly agree: First study: PPA1 I feel that this [TECHNOLOGY] is important for me in terms of volume of usage* PPA2 I feel that I need the benefits this [TECHNOLOGY] offers* PPA3 I feel that I will experience noticeable discomfort if I choose to replace this [TECHNOLOGY] for a substitute* PPA4 There are a lot of alternatives to the current [TECHNOLOGY] [reverse-coded]* PPA5 I feel that I depend on this [TECHNOLOGY] Second study: PPA1 I feel that I depend on the technologies available in the market * PPA2 I feel that I could easily stop using the technologies available in the market if I was concerned about its trustworthiness [reverse coded] * PPA3 I feel that as a consumer I can control and choose the terms under which I am using the technologies available in the market [reverse coded]	Based on theorization by Tirole & Randoll, 2017 & Bodo, 2020; Scale adapted from Wang, 2011; Cronbach's Alpha = 0,78
4. Concern about privacy	Subjective sensation of lack of control over information disclosure and use specifically in relation to the duplication and sharing of information for secondary use	1 to 7 Likert scale from Strongly disagree to Strongly agree: CAP1 It usually bothers me when companies ask me for personal information * CAP2 Companies should devote more time and effort to preventing unauthorized access to personal information * CAP3 Companies should never sell the personal information in their computer databases to other companies * CAP4 I'm concerned that companies are collecting too much personal information about me	Adapted from Smith et al., 1996 - 11; Cronbach's Alpha = 0,82
		Dependent variable	

1. Technology trusting beliefs	1. Competence – having the skills and ability to do a task; 2. Benevolence – being of a caring, considerate nature with intentions of goodwill; 3. Integrity – acceptable principles, being consistent in words and deeds, having a good reputation and sense of justice.	1 to 7 Likert scale from Strongly disagree to Strongly agree: Trusting beliefs in **benevolence**: TRBB1 I believe that the [TECHNOLOGY] would be employed in my best interest * TRBB2 If I required help, the [TECHNOLOGY] would do its best to help me * TRBB3 The [TECHNOLOGY] would be concerned about my well-being, not just its own * Trusting beliefs in **competence**: TRBC1 The [TECHNOLOGY] is competent and effective in storing personal information about citizens * TRBC2 The [TECHNOLOGY] would perform its role of storing personal information about citizens very well TRBC3 Overall, the [TECHNOLOGY] would be a capable and proficient means for identifying citizens TRBC4 In general, the [TECHNOLOGY] would have sufficient information about citizens Trusting beliefs in **integrity:** TRBI1 The [TECHNOLOGY] would be truthful in its dealings with me * TRBI2 I would characterize the [TECHNOLOGY] as honest * TRBI3 The [TECHNOLOGY] would keep its commitments * TRBI4 The [TECHNOLOGY] would be sincere and genuine	Li et al., 2008; Chronbach's Alphas, respectively, for the three trusting beliefs - 0.87, 0.89, 0.92

Figure 4

Video fragment and script for Study 1 / emerging technology condition

Final video is available online, following the link: emerging.

Emerging technology

Modern society relies on a great number of tools, such as sensors. For example, motion sensors allow doors to automatically open and shut. The most promising sensor of the last decade is the nanochip. Nanochips are a combination of nanoelectronic components and living cells. Nano chips of a size smaller than a molecule are injected into the human body, serving multiple healthcare objectives.

This is an emerging technology, meaning, a technology, which is not widely used, not mainstream nor commercialized in healthcare yet. It is currently under development, and expected to be widely available to end-users within the next five to ten years.

The nanochips are being designed to report data in real time about any changes of the person's condition. In addition, these tiny devices could potentially transfer medicines through blood streams directly to the target. In contrast to chemotherapy and conventional drugs, theoretically the sensors may be able to detect cancer or COVID-cells and eliminate them, while not affecting good cells. In another potential application, by turning brain activities into frequencies of light on a display, these particles are expected to diagnose neurological diseases and study previously unreachable brain parts.

But the data from the particles is transmitted to a host server and potentially could be hacked. A hacker then could use the data to access the owner's personal information for blackmailing or scamming purposes. The threat is theoretical, but we are in need of creating viable legislation over the issue, since the biggest nanotechnological manufacturers are very powerful on the market. However, this technology has incredible potential to bring significant benefits to patients and doctors, and it is important to ensure we are able to achieve the benefits so many people can come to need

Figure 5

Video fragment and script for Study 1/ existing technology condition

Final video is available online, following the link: existing.

Existing technology

Modern society relies on a great number of tools, such as sensors. For example, motion sensors allow doors to automatically open and shut. The most promising sensor of the last decades is the nanochip. Nanochips are a combination of nanoelectronic components and living cells. Nano chips of a size smaller than a molecule are injected into the human body, serving multiple healthcare objectives.

This is an existing technology, meaning, a technology, which is widely used, mainstream, and commercialized in healthcare. It was under development, and became widely available to end-users five to ten years ago.

The nanochips were designed to report data in real time about any changes of the person's condition. In addition, these tiny devices transfer medicines through blood streams directly to the target. In contrast to chemotherapy and conventional drugs, the sensors may detect cancer or COVID-cells and eliminate them, while not affecting good cells. In another application, by turning brain activities into frequencies of light on a display, these particles diagnose neurological diseases and study previously unreachable brain parts.

But the data from the particles is transmitted to a host server and potentially could be hacked. A hacker then could use the data to access the owner's personal information for blackmailing or scamming purposes. The threat is theoretical, but we are in need of controlling that the legislation over the issue is applied properly, since the biggest nanotechnological manufacturers are very powerful on the market. However, this technology brings significant benefits to patients and doctors, and it is important to ensure we are able to achieve the benefits so many people can come to need.

Figure 6

Initial factor cross-loadings analysis of constructs in Study 1

	Concern about privacy	Claculus-based trust	Descriptive social norms	Faith in humanity	Gender	Injunctive social norms	Perceived power asymmetry	Situational normality	Structural assurance	Trusting belief in technology	Tech-savviness
CAP2	.022	-.160	.290	.020	-.039	.049	.068	.046	.006	.102	.036
CAP3	.214	-.119	.110	.026	-.069	.050	.007	-.036	-.075	-.073	.035
CAP4	**.972**	-.198	-.059	-.058	.082	-.250	-.147	-.403	-.328	-.398	-.069
CBT1	-.134	**.736**	-.031	.035	-.063	.205	-.005	.114	.140	.170	.015
CBT2	-.151	**.907**	.121	.061	-.032	.310	.083	.289	.345	.273	-.021
DSN1	-.015	.011	**.773**	.108	-.113	.299	.323	.296	.275	.361	-.023
DSN2	-.176	.096	**.886**	.167	-.078	.351	.329	.468	.357	.540	.039
DSN3	.000	.035	.464	.118	-.009	.079	.089	.123	.102	.138	.011
FIHB1	.021	-.024	.073	.445	.036	.087	.133	.020	.064	.097	.003
FIHB2	-.027	-.022	-.003	.387	.000	.074	.108	.072	.026	.063	.062
FIHB3	-.048	-.008	.033	**.600**	-.011	.080	.116	.078	.106	.075	.119
FIHC1	-.094	.142	.137	**.737**	.028	.151	.090	.090	.134	.118	.048
FIHC2	-.020	-.018	-.002	.393	.125	.012	.036	.096	.083	.107	-.045
FIHC3	-.073	.021	.041	.474	.078	.030	.041	.085	.108	.122	-.029
FIHI1	-.036	.024	.096	.532	-.019	.111	.074	.100	.090	.116	.062
FIHI2	.045	-.119	.024	.517	.105	.060	.113	.074	.113	.089	-.075
FIHI3	-.023	.010	-.025	.245	-.052	.079	.023	.034	.061	.086	.120
GENDER	.087	-.052	-.102	.064	**1.000**	-.235	-.136	-.178	-.026	-.107	-.355
ISN1	-.223	.280	.358	.122	-.217	**.895**	.466	**.610**	**.552**	**.559**	.052
ISN2	-.274	.289	.222	.133	-.227	**.852**	.465	.531	.470	.504	.068
ISN3	-.201	.284	.415	.184	-.184	**.912**	**.551**	**.603**	.507	**.560**	.060
PP4_RC	-.054	-.106	.118	.022	-.074	.002	.131	.039	.005	.111	.046
PPA1	-.202	.054	.342	.103	-.116	.498	**.818**	**.596**	.472	**.607**	-.015
PPA2	-.133	.034	.279	.169	-.115	.447	**.835**	**.577**	.496	.479	-.061
PPA3	.009	.187	.111	.110	.008	.169	.428	.243	.189	.303	-.017
PPA5	-.049	.008	.258	.130	-.103	.427	**.713**	.459	.383	.428	-.024
SITNOR1	-.393	.196	.337	.040	-.188	**.555**	.544	**.808**	**.578**	**.647**	.152
SITNOR2	-.335	.205	.390	.066	-.159	**.559**	**.570**	**.824**	**.573**	**.675**	.068
SITNOR3	-.338	.229	.410	.087	-.176	**.576**	**.563**	**.850**	**.570**	**.716**	.136
SITNOR4	-.338	.240	.372	.205	-.065	.476	**.575**	**.818**	**.565**	**.686**	-.053
STRASS1	-.246	.215	.298	.122	-.028	.422	.407	.517	**.757**	.531	-.089
STRASS2	-.299	.332	.249	.125	-.009	.462	.391	**.565**	**.815**	**.613**	-.067
STRASS3	-.246	.183	.327	.164	-.024	.455	.509	.529	**.757**	.548	-.076
TRBB1	-.361	.200	.469	.135	-.059	.495	.538	**.734**	**.551**	**.850**	.014
TRBB2	-.285	.076	.472	.157	-.102	.412	.476	**.553**	.468	**.702**	.112
TRBB3	-.278	.290	.180	.187	-.001	.325	.255	.371	.499	.464	-.092
TRBC1	-.176	.222	.159	.061	-.056	.357	.323	.368	.447	.473	-.038
TRBC2	-.173	.191	.213	.037	.012	.272	.275	.358	.384	.437	-.067
TRBC3	-.013	-.128	.269	.127	-.102	.164	.278	.162	.106	.247	.111
TRBC4	.025	-.062	.355	.023	.023	.099	.127	.139	.034	.171	-.027
TRBI1	-.359	.249	.439	.059	-.074	.481	.549	**.661**	**.601**	**.823**	.034
TRBI2	-.361	.230	.436	.090	-.091	.501	.533	**.660**	**.601**	**.790**	.020
TRBI3	-.285	.084	.410	.075	-.017	.487	.500	**.572**	.515	**.704**	-.048
TRBI4	-.318	.266	.380	.130	-.141	.469	.429	**.578**	**.560**	**.702**	-.031
TSAV1	-.049	.061	.022	.070	-.306	.115	-.005	.072	-.077	.039	**.746**
TSAV10_RC	-.088	-.038	-.053	-.089	-.129	.047	-.023	.041	-.051	.042	.380
TSAV2_RC	-.074	-.028	-.075	-.061	-.159	-.092	-.012	-.008	-.143	-.029	**.558**
TSAV3	.022	.116	-.114	.011	-.246	.118	.037	.069	-.028	-.003	**.662**
TSAV4	-.023	-.050	.104	.022	-.292	.055	-.031	.076	-.068	.024	**.716**
TSAV5	-.112	.026	.019	.061	-.210	.074	-.051	.070	-.062	.042	**.737**
TSAV6	.016	-.005	.099	.017	-.299	.102	.061	.123	.018	.087	**.728**
TSAV7	-.052	-.110	.066	.052	-.259	.043	-.018	.037	-.078	-.003	**.561**
TSAV8_RC	-.069	-.076	-.017	-.090	-.201	-.055	-.144	-.007	-.111	-.029	**.584**
TSAV9	-.046	.049	.029	.108	-.166	.046	-.045	.123	-.004	.050	**.700**

**Factor loadings 0.55 and above bolded as significant, as per Hair et al. (2015)*

Figure 7

Factor cross-loadings analysis of constructs in Study 1 after model alteration

	Concern about privacy	Claculus-based trust	Descriptive social norms	Faith in humanity	Gender	Injunctive social norms	Perceived power asymmetry	Situational normality	Structural assurance	Trusting belief in technology	Tech-savviness
CAP4	**1.000**	-.198	-.059	-.109	.082	-.249	-.156	-.373	-.327	-.389	-.076
CBT1	-.150	**.740**	-.034	.075	-.063	.206	-.023	.120	.137	.183	.020
CBT2	-.177	**.905**	.120	.132	-.032	.309	.076	.286	.345	.283	-.050
DSN1	.024	.010	**.787**	.035	-.113	.300	.310	.300	.277	.363	-.050
DSN2	-.114	.095	**.884**	.147	-.078	.353	.334	.469	.357	.525	.040
DSN3	.033	.035	.433	.126	-.009	.079	.072	.115	.105	.127	.004
FIHB1	.027	-.024	.075	.423	.036	.088	.128	.028	.064	.141	-.005
FIHB3	-.062	-.009	.033	.535	-.011	.080	.093	.088	.105	.073	.110
FIHC1	-.087	.142	.132	**.903**	.028	.151	.095	.103	.134	.131	.036
FIHC3	-.053	.022	.034	.549	.078	.031	.034	.114	.108	.123	-.040
FIHI1	-.023	.024	.095	.487	-.019	.111	.053	.104	.092	.143	.064
FIHI2	.043	-.119	.023	.512	.105	.061	.107	.092	.114	.088	-.119
GENDER	.082	-.053	-.104	-.000	**1.000**	-.235	-.138	-.158	-.026	-.114	-.346
ISN1	-.204	.280	.362	.124	-.217	**.898**	.487	**.595**	**.551**	**.570**	.019
ISN2	-.270	.289	.223	.155	-.227	**.847**	.465	.505	.471	.485	.047
ISN3	-.193	.284	.418	.154	-.184	**.914**	**.556**	**.580**	.508	**.559**	.016
PPA1	-.178	.054	.348	.041	-.116	.498	**.846**	**.571**	.476	**.581**	-.019
PPA2	-.129	.034	.281	.095	-.115	.448	**.839**	**.578**	.497	.454	-.079
PPA5	-.029	.008	.259	.126	-.103	.428	**.726**	.438	.385	.436	-.044
SITNOR2	-.321	.205	.391	.051	-.159	**.559**	**.566**	**.846**	**.573**	**.643**	.040
SITNOR3	-.321	.229	.411	.107	-.176	**.576**	**.556**	**.858**	**.568**	**.664**	.113
SITNOR4	-.311	.239	.374	.177	-.065	.477	**.580**	**.846**	**.566**	**.656**	-.071
STRASS1	-.241	.215	.298	.108	-.028	.423	.411	.519	**.750**	.543	-.111
STRASS2	-.296	.331	.254	.136	-.009	.463	.396	.542	**.808**	**.622**	-.102
STRASS3	-.223	.182	.326	.109	-.024	.455	.514	.499	**.771**	**.568**	-.091
TRBB2	-.250	.076	.474	.148	-.102	.413	.462	**.550**	.468	**.699**	.079
TRBI1	-.320	.249	.441	.043	-.074	.481	.535	**.650**	**.602**	**.830**	.022
TRBI2	-.318	.230	.436	.088	-.091	.501	.511	**.653**	**.600**	**.819**	.006
TRBI3	-.247	.083	.413	.045	-.017	.487	.491	**.576**	.517	**.721**	-.059
TRBI4	-.295	.266	.384	.127	-.141	.470	.426	**.571**	**.560**	**.754**	-.069
TSAV1	-.048	.061	.018	.150	-.306	.115	.007	.056	-.076	.015	**.730**
TSAV2_RC	-.083	-.027	-.074	-.004	-.159	-.093	-.026	-.037	-.142	-.045	**.674**
TSAV3	.025	.116	-.112	.098	-.246	.118	.041	.057	-.028	-.002	**.602**
TSAV4	-.019	-.050	.101	.106	-.292	.055	-.030	.066	-.066	.024	**.712**
TSAV5	-.114	.027	.017	.081	-.210	.074	-.062	.060	-.062	.038	**.699**
TSAV6	.017	-.006	.097	.062	-.299	.101	.037	.083	.017	.089	**.629**
TSAV7	-.028	-.110	.066	.134	-.259	.043	-.009	.035	-.078	-.031	**.573**
TSAV8_RC	-.046	-.076	-.018	-.043	-.201	-.055	-.137	-.036	-.113	-.035	**.653**
TSAV9	-.036	.049	.027	.116	-.166	.046	-.054	.080	-.004	.047	**.585**

**Factor loadings 0.55 and above bolded as significant, as per Hair et al. (2015)*

Figure 8

Heterotrait-montrait ratio (HTMT) analysis of constructs in Study 1

	Concern about privacy	Calculus-based trust	Desciptive social norms	Faith in humanity	Gender	Institutional-based trust	Injunctive social norms	Perceived power asymmetry	Trusting beliefs in technology	Technolo-gical savviness
CAP										
CBT	.264									
DSN	.099	.151								
FIH	.101	.196	.194							
GENDER	.082	.077	.116	.077						
IBT	.437	.412	.570	.189	.143					
ISN	.270	.449	.454	.203	.254	.797				
PPA	.161	.093	.481	.187	.160	.839	.706			
TRB	.382	.345	.593	.197	.104	.899	.674	.729		
TSAV	.075	.139	.168	.205	.385	.164	.135	.107	.081	

Figure 9

Descriptive statistics and construct reliability in Study 1

		Mean	St.Dev.	Chronbach's Alpha	Average variance extracted (AVE)	Collinearity statistics (VIF)
Concern about privacy	**CAP4**	5.144	1.496	**1****		1.000
Calculus-based trust	**CBT1**	3.410	1.568	.553	**.677**	1.171
	CBT2	3.084	1.571			1.171
Desciptive social norms	**DSN1**	4.865	1.226	**.600**	**.709**	1.225
	DSN2	4.809	1.073			1.225
Faith in humanity	**FIHB3**	4.064	1.328	**.727**	**.535**	1.473
	FIHC1	4.454	1.161			1.404
	FIHC3	4.884	1.149			1.491
	FIHI1	4.056	1.223			1.327
	FIHI2	4.263	1.260			1.284
Injunctive social norms	**ISN1**	3.689	1.464	**.864**	**.786**	2.475
	ISN2	3.367	1.375			1.888
	ISN3	3.681	1.381			2.752
Perceived power asymmetry	**PPA1**	3.721	1.354	.588	.411	1.476
	PPA2	4.147	1.394			1.540
	PPA5	3.267	1.460			1.469
Situational normality	**SITNOR2**	4.032	1.463	**.808**	**.723**	1.727
	SITNOR3	4.008	1.299			1.795
	SITNOR4	4.088	1.357			1.758
Structural assurance	**STRASS1**	3.968	1.425	**.671**	**.603**	1.298
	STRASS2	3.542	1.395			1.377
	STRASS3	3.952	1.396			1.266
Trusting beliefs in technology	**TRBB2**	4.458	1.205	**.849**	**.627**	1.413
	TRBI1	4.139	1.198			2.087
	TRBI2	4.084	1.258			2.300
	TRBI3	4.120	1.263			2.105
	TRBI4	4.028	1.270			1.735
Technological savviness	**TSAV1**	3.964	1.552	**.857**	**.627**	1.724
	TSAV2_RC	4.526	1.384			1.735
	TSAV3	3.307	1.511			1.622
	TSAV4	4.904	1.480			1.717
	TSAV5	4.729	1.466			1.720
	TSAV6	4.514	1.550			1.928
	TSAV7	4.538	1.454			1.342
	TSAV8_RC	5.271	1.556			1.715
	TSAV9	5.558	1.184			1.764

**AVE > 0.5 are bolder significant, as per Mendes dos Santos & Cirillo (2021)*
***Chronbach's Alphas > 0.6 are bolded significant, as per Nunally & Bernstein (1994)*

Figure 10

Support of structural model assessment hypotheses in Study 1

Hypothesis	Supported?
H1: There is a significant negative relation between faith in humanity and perceived power asymmetry	?
H2: There is a significant positive relation between perceived power asymmetry and concern about privacy	?
H3: There is a significant negative relation between concern about privacy and trusting beliefs in technology	✓
H4: There is a significant positive relation between injunctive social norms and trusting beliefs in technology	✕
H5: There is a significant positive relation between descriptive social norms and trusting beliefs in technology	✓
H6: There is a significant positive relation between calculus-based trust and trusting beliefs in technology	?
H7: There is a significant positive relation between faith in humanity and situational normality (applied to technology)	✕
H8: There is a significant positive relation between technological savviness and situational normality (applied to technology)	✕
H9: There is a significant positive relation between structural assurance (applied to technology) and trusting beliefs in technology	✓
H10: There is a significant positive relation between situational normality (applied to technology) and trusting beliefs in technology	✓

Figure 11

Video fragment and script for Study 2 / bionano condition

Final video is available online, following the link: bionano.

Bionano technology

Modern society relies on a great number of tools, such as sensors. For example, motion sensors allow doors to automatically open and shut. The most promising technology of the last 5 years is the nanochip. Nanochips are a combination of nanoelectronic components and living cells. Nano chips of a size smaller than a molecule are injected into the human body, serving multiple healthcare objectives.

The particles can report data in real time about any changes of the person's condition. These tiny devices can transfer drugs through blood streams directly to the target. In contrast to chemotherapy and conventional drugs, the sensors may detect cancer or covid cells and eliminate them, while not affecting good cells. By turning brain activities into frequencies of light on a display, these particles will be able to diagnose neurological diseases and study previously unreachable brain parts.

But the data from the particles is transmitted to a host server and potentially, could be hacked. A hacker then could use the data to access owner's personal information for blackmailing or scamming purposes. The threat is theoretical, but we are in need of creating viable legislation over the issue, since the biggest nanotechnological manufacturers are very powerful on the market.

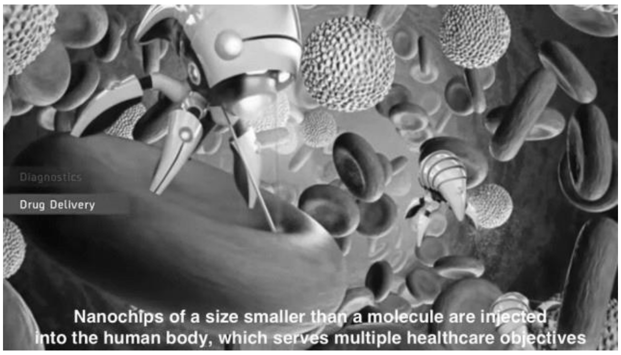


Figure 12

Video fragment and script for Study 2 / smartphone condition

Final video is available online, following the link: smartphone.

Smartphone technology

Modern society relies on a great number of tools, such as communication ones. For example, e-mail and social networks allow for easy connection to people. The most promising technology of the last 10 years is the smartphone. Smartphones are a combination of an electronic communicator with various applications. Smartphones of various sizes are used, serving multiple life objectives.

Smartphones ensure a better routine, by connecting friends and family, and resolving work and business issues. These small devices can store personal information and data from all life spheres. In contrast to conventional maps and navigational tools, GPS apps make getting around easy, while avoiding traffic jams. By aggregating different functions in one single place, these devices are also able to capture best moments of our lives with their built-in cameras and share them online.

But the data from smartphones is transmitted to host servers and, potentially, could be hacked. A hacker then could use the data to access owner's personal information for blackmailing or scamming purposes. This threat is theoretical, but we are in need of proper control over the issue, since the biggest smartphone manufacturers are very powerful on the market.

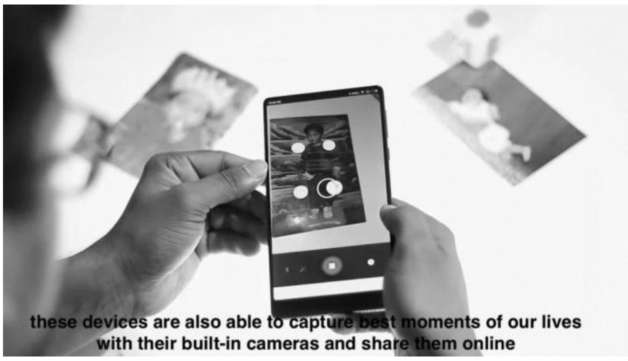


Figure 13

Initial factor cross-loadings analysis of constructs in Study 2

	Concern about privacy	Calculus-based trust	Desciptive social norms	Faith in humanity	Injunctive social norms	Perceived power asymmetry	Situational normality	Structural assurance	Trusting beliefs in technology	Technolo-gical savviness
CAP1	**.851**	-.181	-.048	-.056	-.166	.255	-.249	-.248	-.318	-.007
CAP2	.443	-.119	.139	.105	-.024	.146	-.023	-.043	-.032	.014
CAP3	.261	-.027	.066	.002	-.005	.038	.025	-.033	-.010	.111
CAP4	**.877**	-.364	.018	-.049	-.106	.262	-.269	-.278	-.353	.051
CBT1	-.243	**.871**	.051	.209	.166	-.265	.266	.326	.403	.049
CBT2	-.304	**.879**	.047	.179	.249	-.376	.272	.382	.416	-.004
DSM1	.048	.080	**.796**	.031	.508	-.094	**.566**	.435	.252	.008
DSM2	-.078	.088	**.880**	.110	.505	-.152	**.605**	.484	.422	.049
DSM3	.105	-.064	**.633**	.080	.268	-.075	.316	.268	.256	.110
FIHB1	.007	.102	-.004	**.751**	.096	-.001	.097	.126	.122	.027
FIHB2	-.037	.182	.043	**.714**	.115	-.130	.168	.202	.219	.086
FIHB3	-.003	.113	.102	**.774**	.136	-.104	.156	.197	.243	.103
FIHC1	-.077	.212	.043	**.731**	.035	-.141	.149	.214	.240	.057
FIHC2	-.037	.199	.100	**.727**	.098	-.145	.186	.225	.257	.027
FIHC3	-.052	.131	.153	**.665**	.090	-.118	.128	.163	.241	.001
FIHI1	-.020	.133	.061	**.711**	.116	-.048	.144	.194	.176	.077
FIHI2	-.007	.161	-.004	**.732**	.044	-.120	.128	.194	.225	.123
FIHI3	-.015	.170	.154	**.755**	.184	-.048	.154	.169	.192	.022
ISN2	-.183	.250	.333	.105	**.873**	-.281	.470	.459	.439	.119
ISN3	-.084	.175	**.640**	.136	**.897**	-.189	**.686**	**.578**	.484	.089
PPA1	.016	.153	**.660**	.051	**.633**	-.103	**.630**	.486	.330	.048
PPA2_RC	.123	-.235	.003	-.075	-.069	**.576**	-.168	-.225	-.247	-.161
PPA3 _RC	.303	-.332	-.161	-.135	-.269	**.937**	-.439	-.507	-.482	-.102
SITNOR1	-.222	.228	**.681**	.153	**.617**	-.350	**.882**	**.718**	**.584**	.216
SITNOR2	-.264	.277	**.578**	.218	**.609**	-.399	**.919**	**.797**	**.710**	.244
SITNOR3	-.268	.294	.480	.145	**.567**	-.376	**.860**	**.715**	**.682**	.209
SITNOR4	-.232	.285	**.580**	.206	.542	-.430	**.875**	**.712**	**.687**	.199
STRASS1	-.266	.322	.423	.240	.501	-.418	**.697**	**.878**	**.674**	.116
STRASS2	-.267	.381	.495	.207	**.554**	-.472	**.778**	**.901**	**.706**	.153
STRASS3	-.239	.376	.469	.257	.516	-.486	**.746**	**.886**	**.677**	.163
TRBB1	-.333	.408	.328	.247	.410	-.400	**.646**	**.643**	**.830**	.143
TRBB2	-.181	.222	.422	.206	.446	-.308	**.621**	**.571**	**.700**	.181
TRBB3	-.247	.296	-.217	.126	.050	-.318	.133	.242	.467	.080
TRBC1	-.262	.346	.416	.186	.417	-.301	.545	**.552**	**.618**	.161
TRBC2	-.096	.211	.404	.200	.360	-.202	.469	.440	.528	.173
TRBC3	.019	.080	.403	.088	.320	-.077	.367	.318	.353	.034
TRBI1	-.361	.373	.125	.219	.303	-.431	.464	.501	**.724**	.144
TRBI2	-.332	.440	.169	.254	.359	-.459	.510	**.579**	**.775**	.135
TRBI3	-.276	.356	.335	.252	.356	-.436	**.616**	**.633**	**.803**	.190
TRBI4	-.283	.346	.315	.202	.416	-.358	**.559**	**.576**	**.797**	.147
TSAV1	-.005	-.013	.002	.020	.082	-.148	.163	.137	.150	**.797**
TSAV10_RC	-.019	-.015	.070	.029	.152	-.062	.190	.131	.156	**.624**
TSAV2_RC	.046	-.062	-.049	-.078	-.091	-.015	-.027	-.082	-.035	.509
TSAV3	-.013	.060	.054	.063	.192	-.177	.226	.192	.181	**.780**
TSAV4	.077	-.077	.026	-.028	-.025	-.034	.085	-.012	.023	**.695**
TSAV5	.084	.020	.045	.072	.090	-.140	.214	.125	.166	**.823**
TSAV6	.021	.072	.038	.119	.055	-.091	.194	.155	.209	**.844**
TSAV7	.006	.028	.038	.066	.023	-.071	.128	.039	.110	**.714**
TSAV8_RC	-.001	-.099	.039	-.004	-.062	-.013	.076	.005	.067	**.558**
TSAV9	.077	.032	.106	.089	.062	-.109	.201	.100	.177	**.765**

**Factor loadings 0.55 and above bolded as significant, as per Hair et al. (2015)*

Figure 14

Factor cross-loadings analysis of constructs in Study 2 after model alteration

	Concern about privacy	Calculus-based trust	Desciptive social norms	Faith in humanity	Injunctive social norms	Perceived power asymmetry	Situational normality	Structural assurance	Trusting beliefs in technology	Technolo-gical savviness
CAP1	**.864**	-.181	-.05	-.056	-.166	.256	-.249	-.248	-.324	-.007
CAP4	**.886**	-.364	.016	-.049	-.093	.264	-.27	-.278	-.362	.052
CBT1	-.252	**.869**	.051	.209	.172	-.264	.266	.326	.402	.047
CBT2	-.3	**.88**	.047	.179	.244	-.373	.273	.382	.419	-.005
DSM1	.035	.08	**.789**	.031	.549	-.081	**.565**	.436	.203	.007
DSM2	-.097	.088	**.886**	.11	**.565**	-.143	**.604**	.484	.368	.046
DSM3	.081	-.065	**.63**	.08	.296	-.073	.315	.268	.216	.11
FIHB1	-.009	.102	-.004	**.751**	.086	0	.097	.125	.111	.026
FIHB2	-.063	.182	.041	**.713**	.1	-.128	.168	.202	.219	.085
FIHB3	-.019	.113	.103	**.774**	.133	-.104	.155	.197	.227	.102
FIHC1	-.095	.212	.044	**.731**	.06	-.142	.15	.214	.234	.053
FIHC2	-.044	.199	.102	**.728**	.119	-.145	.186	.225	.252	.023
FIHC3	-.067	.131	.155	**.666**	.129	-.119	.128	.163	.24	-.003
FIHI1	-.022	.133	.061	**.71**	.108	-.047	.145	.194	.171	.075
FIHI2	-.025	.161	-.003	**.732**	.057	-.121	.128	.195	.238	.121
FIHI3	-.025	.17	.154	**.754**	.182	-.045	.154	.169	.199	.024
ISN1	-.117	.21	**.632**	.147	**.927**	-.234	**.639**	**.556**	.488	.111
ISN2	-.18	.251	.333	.105	**.795**	-.275	.47	.46	.401	.117
ISN3	-.097	.175	**.639**	.136	**.916**	-.178	**.686**	**.578**	.439	.085
PPA2_RC	.116	-.236	.004	-.075	-.08	**.569**	-.168	-.225	-.258	-.162
PPA3 _RC	.301	-.332	-.162	-.135	-.27	**.94**	-.439	-.507	-.48	-.099
SITNOR1	-.242	.228	**.679**	.153	**.657**	-.34	**.88**	**.718**	.535	.213
SITNOR2	-.283	.277	**.578**	.218	**.635**	-.39	**.919**	**.797**	**.668**	.241
SITNOR3	-.272	.294	.48	.145	**.577**	-.37	**.861**	**.715**	**.647**	.205
SITNOR4	-.25	.284	**.58**	.206	**.554**	-.422	**.875**	**.713**	**.65**	.196
STRASS1	-.28	.322	.424	.24	**.513**	-.413	**.697**	**.876**	**.634**	.112
STRASS2	-.276	.381	.496	.207	**.574**	-.465	**.778**	**.901**	**.671**	.148
STRASS3	-.248	.376	.468	.257	**.523**	-.48	**.746**	**.887**	**.655**	.162
TRBB1	-.355	.408	.329	.247	.441	-.397	**.647**	**.643**	**.843**	.142
TRBI1	-.369	.373	.128	.219	.295	-.431	.464	.501	**.767**	.142
TRBI2	-.343	.44	.172	.254	.368	-.457	.511	**.579**	**.823**	.133
TRBI3	-.289	.356	.337	.252	.396	-.433	**.616**	**.633**	**.819**	.186
TRBI4	-.303	.346	.317	.202	.45	-.355	**.56**	**.576**	**.811**	.144
TSAV1	.007	-.013	.003	.02	.08	-.147	.163	.137	.131	**.794**
'SAV10_RC	-.027	-.015	.07	.029	.145	-.06	.19	.132	.155	**.63**
TSAV3	-.005	.06	.054	.063	.177	-.174	.226	.193	.177	**.783**
TSAV4	.069	-.077	.026	-.028	-.023	-.035	.085	-.012	.01	**.694**
TSAV5	.089	.02	.046	.072	.093	-.139	.214	.125	.154	**.821**
TSAV6	.013	.072	.038	.119	.07	-.09	.194	.155	.207	**.844**
TSAV7	-.002	.027	.04	.066	.031	-.071	.128	.039	.09	**.711**
TSAV9	.058	.032	.107	.089	.08	-.109	.201	.1	.163	**.764**

**Factor loadings 0.55 and above bolded as significant, as per Hair et al. (2015)*

Figure 15

Heterotrait-montrait ratio (HTMT) analysis of constructs in Study 2

	Concern about privacy	Calculus-based trust	Desciptive social norms	Faith in humanity	Injunctive social norms	Perceived power asymmetry	Institutional-based trust	Trusting beliefs in technology	Technolo-gical savviness
CAP									
CBT	.448								
DSN	.137	.146							
FIH	.074	.272	.132						
IBT	.386	.451	.771	.255					
ISN	.196	.312	.789	.169	.757				
PPA	.496	.672	.232	.204	.704	.379			
TRB	.515	.599	.377	.311	.796	.546	.790		
TSAV	.078	.085	.127	.112	.212	.128	.244	.186	

Figure 16

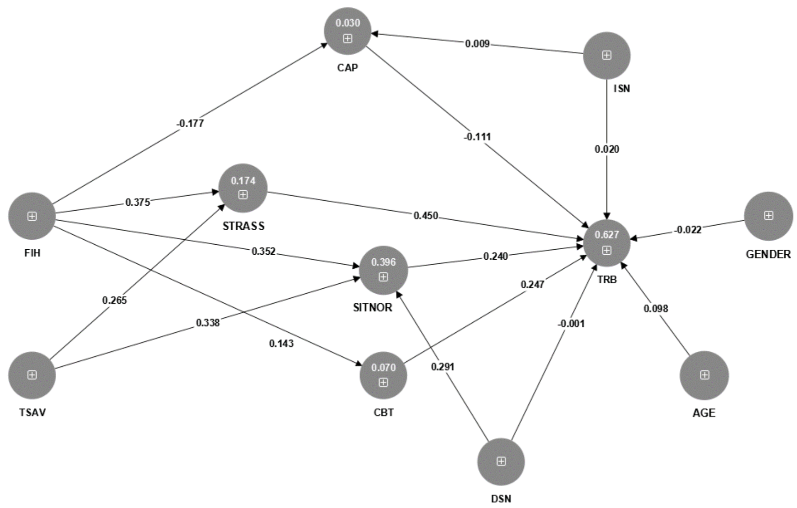
Descriptive statistics and construct reliability in Study 2

		Mean	St.Dev.	Chronbach's Alpha	Average variance extracted (AVE)	Cillinearity statistics (VIF)
Concern about privacy	**CAP1**	5.267	1.393	**.694****	**.765***	1.393
	CAP4	5.571	1.402			1.393
Calculus-based trust	**CBT1**	3.386	1.603	**.694**	**.766**	1.393
	CBT2	2.918	1.569			1.393
Desciptive social norms	**DSM1**	4.537	2.408	**.671**	**.597**	1.594
	DSM2	4.889	1.309			1.556
	DSM3	5.468	1.241			1.143
Faith in humanity	**FIHB1**	4.638	1.221	**.891**	**.532**	2.775
	FIHB2	4.167	1.310			2.071
	FIHB3	4.529	1.157			2.364
	FIHC1	4.902	1.048			2.130
	FIHC2	5.262	1.022			2.513
	FIHC3	5.185	1.060			2.343
	FIHI1	4.339	1.200			2.301
	FIHI2	4.503	1.189			1.792
	FIHI3	4.413	1.215			2.402
Injunctive social norms	**ISN1**	4.190	1.636	**.854**	**.777**	3.241
	ISN2	3.484	1.489			1.558
	ISN3	4.325	1.733			3.161
Perceived power asymmetry	**PPA2_RC**	4.312	1.837	.406	**.604**	1.070
	PPA3 _RC	4.328	1.668			1.070
Situational normality	**SITNOR1**	4.423	1.905	**.907**	**.781**	2.955
	SITNOR2	4.312	1.516			3.551
	SITNOR3	3.868	1.476			2.292
	SITNOR4	4.259	1.379			2.464
Structural assurance	**STRASS1**	3.944	1.513	**.866**	**.789**	2.128
	STRASS2	3.788	1.481			2.446
	STRASS3	4.024	1.518			2.231
Trusting beliefs in technology	**TRBB1**	4.286	1.439	**.880**	**.676**	2.218
	TRBI1	4.066	1.307			1.933
	TRBI2	4.016	1.258			2.206
	TRBI3	4.175	1.248			1.961
	TRBI4	4.045	1.320			2.052
Technological savviness	**TSAV1**	4.376	1.646	**.897**	**.546**	2.538
	TSAV10_RC	4.262	1.534			1.445
	TSAV3	3.688	1.739			2.225
	TSAV4	5.429	1.269			2.472
	TSAV5	4.812	1.482			2.327
	TSAV6	4.804	1.560			2.492
	TSAV7	5.090	1.326			2.161
	TSAV9	5.278	1.058			2.200

**AVE > 0.5 bolded as significant, as per Mendes dos Santos & Cirillo (2021)*
***Chronbach's Alphas > 0.6 bolded as significant, as per Nunally & Bernstein (1994)*

Figure 17

*Individual paths estimates for structural model under **smartphone** condition in Study 2*

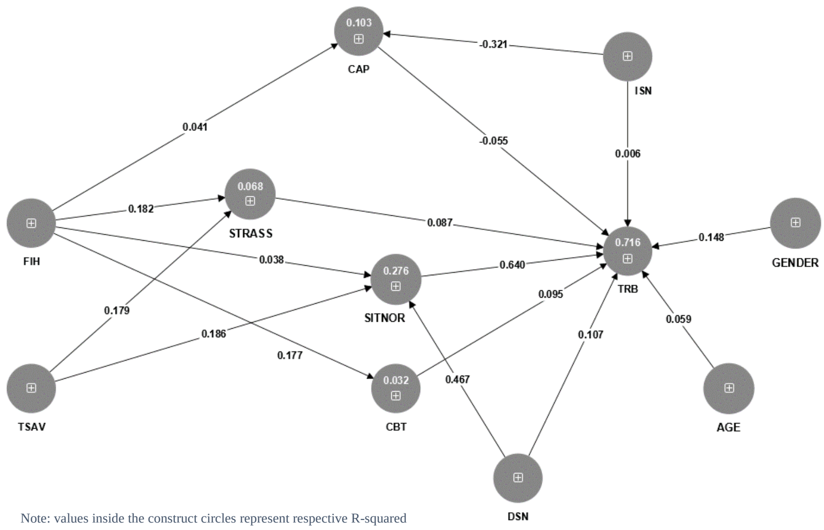


*Values inside the construct circles represent respective R-squared

Note: values inside the construct circles represent respective R-squared

Figure 18

*Individual paths estimates for structural model under **bionano** condition in Study 2*



Note: values inside the construct circles represent respective R-squared

Figure 19

Path coefficients – confidence intervals (bias-corrected) between conditions in Study 2

Relations		Test Stat.	2.5% (smartphone g.)	97.5% (smartphone g.)	2.5% (bionano g.)	97.5% (bionano g.)
AGE	➤	TRB	.003	.198	-.024	.148
CAP	➤	TRB	-.206	-.018	-.155	.037
CBT	➤	TRB	.140	.360	.013	.179
DSN	➤	SITNOR	.148	.407	.329	.575
DSN	➤	TRB	-.122	.138	.000	.203
FIH	➤	CAP	-.310	-.032	-.090	.169
FIH	➤	CBT	.108	.399	.007	.324
FIH	➤	SITNOR	.209	.495	-.083	.163
FIH	➤	STRASS	.199	.524	.035	.326
GENDER	➤	TRB	-.195	.162	-.016	.308
ISN	➤	CAP	-.187	.252	-.466	-.143
ISN	➤	TRB	-.092	.126	-.110	.126
SITNOR	➤	TRB	.088	.394	.442	.812
STRASS	➤	TRB	.303	.585	-.090	.271
TSAV	➤	SITNOR	.204	.463	.063	.281
TSAV	➤	STRASS	.001	.267	.026	.280

Note: significantly different paths are highlighted in grey

Figure 20

Bootstrapping results for individual paths estimates between conditions in Study 2

Relations		Test Stat.	Original (smartphone g.)	Original (bionano g.)	Mean (smartphone g.)	Mean (bionano g.)	SD (smartphone g.)	SD (bionano g.)	t-value (smartphone g.)	t-value (bionano g.)	p-value (smartphone g.)	p-value (bionano g.)
AGE	➤	TRB	.098	.059	.097	.058	.049	.044	2.009	1.347	.045	.178
CAP	➤	TRB	-.111	-.055	-.108	-.055	.048	.049	2.301	1.134	.021	.257
CBT	➤	TRB	.247	.095	.244	.098	.056	.042	4.405	2.244	.000	.025
DSN	➤	SITNOR	.291	.467	.294	.469	.066	.061	4.414	7.595	.000	.000
DSN	➤	TRB	-.001	.107	-.003	.107	.066	.052	0.012	2.063	.990	.039
FIH	➤	CAP	-.177	.041	-.176	.040	.071	.066	2.491	0.611	.013	.541
FIH	➤	CBT	.265	.179	.265	.181	.074	.081	3.595	2.220	.000	.026
FIH	➤	SITNOR	.352	.038	.345	.037	.073	.063	4.806	0.605	.000	.545
FIH	➤	STRASS	.375	.182	.371	.182	.082	.074	4.564	2.457	.000	.014
GENDER	➤	TRB	-.022	.148	-.027	.148	.091	.081	0.246	1.826	.806	.068
ISN	➤	CAP	.009	-.321	.003	-.326	.110	.081	0.079	3.970	.937	.000
ISN	➤	TRB	.020	.006	.026	.005	.057	.061	0.349	0.105	.727	.916
SITNOR	➤	TRB	.240	.640	.244	.637	.078	.093	3.060	6.847	.002	.000
STRASS	➤	TRB	.450	.087	.446	.088	.073	.091	6.180	0.956	.000	.339
TSAV	➤	SITNOR	.338	.186	.343	.201	.065	.057	5.171	3.274	.000	.001
TSAV	➤	STRASS	.143	.177	.150	.197	.068	.065	2.092	2.738	.037	.006

Note: significantly different paths are highlighted in grey

Figure 21

Bootstrapping results for paths estimates differences with moderation of age in Study 2

			Bootstrap MGA		
		Test Stat.	Difference in path coefficients	1-tailed p-value	2-tailed p-value
Relations					
CAP	➤	TRB	-.135	.974	.052
CBT	➤	TRB	-.078	.858	.284
DSN	➤	SITNOR	.036	.278	.556
DSN	➤	TRB	-.127	.857	.287
FIH	➤	CAP	.011	.459	.919
FIH	➤	CBT	.164	.068	.136
FIH	➤	SITNOR	.069	.203	.407
FIH	➤	STRASS	.182	.041	.083
GENDER	➤	TRB	-.178	.930	.139
GROUP_RC	➤	TRB	-.160	.805	.390
ISN	➤	CAP	.102	.188	.377
ISN	➤	TRB	.096	.163	.326
SITNOR	➤	TRB	-.249	.936	.128
STRASS	➤	TRB	.164	.121	.243
TSAV	➤	SITNOR	-.147	.977	.046
TSAV	➤	STRASS	-.044	.651	.697

Note: significantly different paths are highlighted in grey

Figure 22

Simple slope analysis for TSAV → SITNOR under moderation of age in Study 2

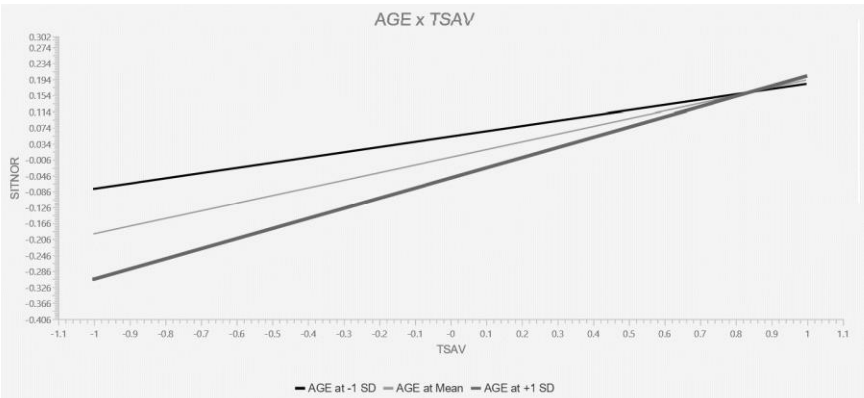


Figure 23

Paths estimates difference in MGA between conditions by faith / confidence predictor groups in Study 2

Relation	Existing technology	Emerging technology	Significant difference?	Stronger for existing technology?	Stronger for emerging technology?
Individual differences					
FIH ➤ CAP	-.177''	$.041^{NS}$	✓	✓	-
FIH ➤ SITNOR	.265'	.179''	✕	-	-
FIH ➤ CBT	.352'	$.038^{NS}$	✓	✓	-
FIH ➤ PPA	?	?	?	-	-
FIH ➤ STRASS	.375'	.182'	✕	-	-
TSAV ➤ SITNOR	.338'	.186'	✕	-	-
TSAV ➤ STRASS	.143''	.177''	✕	-	-
Confidence predictors					
STRASS ➤ TRB	.450'	$.087^{NS}$	✓	✓	-
CBT ➤ TRB	.247'	.095''	✓	✓	-
DSN ➤ SITNOR	.291'	.467'	✕	-	-
DSN ➤ TRB	$-.001^{NS}$	.107''	✕	-	-
Faith predictors					
PPA ➤ CAP	?	?	?	-	-
CAP ➤ TRB	-.111'	$-.055^{NS}$	✕	-	-
ISN ➤ CAP	$.020^{NS}$	-.321'	✓	-	✓
ISN ➤ TRB	$.009^{NS}$	$.006^{NS}$	✕	-	-
SITNOR ➤ TRB	.240''	.640'	✓	-	✓

Note: ' – at p-value < .001
'' – at p-value < .05
NS – not significant at p-value = .005

Figure 24

Support of hypotheses in Studies 1 and 2

Hypothesis	Supported? Study 2	Study 1
H1: There is a significant negative relation between faith in humanity and perceived power asymmetry	**?**	**?**
H1a: The strength of the relation is significantly bigger for the emerging technology than for the existing one	?	?
H2: There is a significant positive relation between perceived power asymmetry and concern about privacy	**?**	**?**
H2a: The strength of the relation between perceived power asymmetry and concern about privacy is significantly bigger for the emerging technology in comparison to the existing one	?	?
H3: There is a significant negative relation between concern about privacy and trusting beliefs in technology	**✓**	**✓**
H3a: The strength of the relation between concern about privacy and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one	✗	?
H4: There is a significant positive relation between injunctive social norms and trusting beliefs in technology	**✗**	**✗**
H4a: The strength of the relation between injunctive social norms and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one	✗	?
H5: There is a significant positive relation between descriptive social norms and trusting beliefs in technology	**✗**	**✓**
H5a: The strength of the relation between descriptive social norms and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one	✗	?
H6: There is a significant positive relation between calculus-based trust and trusting beliefs in technology	**✓**	**?**
H6a: The strength of the relation between calculus-based trust and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one	✓	?
H7: There is a significant positive relation between faith in humanity and situational normality (applied to technology)	**✓**	**✗**
H7a: The strength of the relation between faith in humanity and situational normality (applied to technology) is significantly bigger for the emerging technology in comparison to the existing one	✓	?
H8: There is a significant positive relation between technological savviness and situational normality (applied to technology)	**✓**	**✗**
H8a: The strength of the relation between tech-savviness and situational normality (applied to technology) is significantly bigger for the existing technology in comparison to the emerging one	✗	?
H9: There is a significant positive relation between structural assurance (applied to technology) and trusting beliefs in technology	**✓**	**✓**
H9a: The strength of the relation between structural assurance and trusting beliefs in existing technology is significantly bigger in comparison to the emerging one	✓	?
H10: There is a significant positive relation between situational normality (applied to technology) and trusting beliefs in technology	**✓**	**✓**
H10a: The strength of the relation between situational normality and trusting beliefs in emerging technology is significantly bigger in comparison to the existing one	✓	?

Additional observations		
There is a significant negative relation between injunctive social norms and concern about privacy	**✓**	**✓**
There is a significant positive relation between descriptive social norms and situational normality (applied to technology)	**✓**	**✓**
There is a significant positive relation between faith in humanity and structural assurance	**✓**	**✓**
There is a significant positive relation between technological savviness and structural assurance	**✓**	**✗**