Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn: Hanna B. H. Salvesen og Helena Tournaire Møller

Informasjon fra deltaker

Tittel *:	Trusting Artificial Intelligence: How Perceived Situational Risk and Digital Mindset Can Influence Individuals Decision to Rely
Navn på veileder *:	Elizabeth Solberg

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	41
Andre medlemmer i gruppen:	

Acknowledgements

First and foremost, we would like to thank our supervisor Elizabeth Solberg for all her support and guidance throughout this process. We have gotten the opportunity to make the thesis our own. Still, we are grateful for all her valuable feedback, ideas, and flexibility that has been dedicated to us. We appreciate all we have learned about the interesting topics within this field of research. In addition, we also want to use this opportunity to thank all the participants who took part in our survey, which made writing this thesis possible. Thank you for taking your time.

Abstract

In this thesis, we aim to investigate how domains of perceived situational risk will influence an individual's decision to rely on an artificially intelligent decision aid to perform a decision-making task. We also aim to investigate how an individual's digital mindset beliefs can make the risk factors inherent in the situation more salient. We draw from research on organizational trust, trust in AI technology and decision aids, and implicit theories of mindsets to explore this connection. Our study examined 192 participants' digital mindset and their perceptions of situational risk using an experimental vignette design survey. In our results, we uncovered that there is a negative relationship between specific domains of perceived situational risk and the decision to rely on artificially decision aids. However, our results suggesting that an individual's fixed digital mindset can make certain risk factors inherent in a situation more salient were not supported. These results are reviewed and discussed in terms of their limitations, directions for future research, and practical implications.

Table of Contents

1.0 Introduction

1.1 Problem Identification

In the last few decades, developments of artificially intelligent (AI) technology and scholars predict a future where individuals in corporations will work with AI-embedded programs to assist in the process of organizational decision-making tasks (Metcalf et al., 2019; Shrestha et al., 2019). The organizational push towards a more digital workplace transformation is driven by the belief that technologies can potentially provide innovative and competitive advantages. Yet, the success of this transformation is relatively determined by the extent to which individuals adopt the technology by accepting and using it (Legris et al., 2003), thus it is considered essential for individuals to trust in and rely on the artificially intelligent decision aid (AI decision aid) to carry out the task it is intended to do (Solberg et al., 2022). Still, defining and measuring trust in and reliance on AI-embedded technology has been one of the greatest challenges in this area of research (French et al., 2018).

Mayer et al. (1995) describe trust as a willingness to be vulnerable to the actions of another party, which signifies that there is a willingness to take risk when trusting another party. Therefore, trust is evident when a trustor is willing to allow another party to perform an important action for the trustor. Similarly, research addresses the importance of trust when working with technology to create effective relationships (Hancock et al., 2011), especially with AI-embedded technology that can facilitate organizational decision-making tasks (Glikson & Woolley, 2020). The trust an individual develops towards AI technology will be crucial to establish the role of the technology in organizations progressing forward (Hancock et al., 2011), as this will affect the individual’s decision of relying on the technology.

Moreover, as trust reflects the willingness to put oneself at risk, it indicates the significance of understanding the concept of risk concerning trust. Perceived situational risk has been identified as a fundamental element in research on trust in AI-embedded systems and similar technology (Glikson & Woolley, 2020; Hoff & Bashir, 2015). It is described as an individual’s beliefs about a specific task potentially having negative outcomes because of the experience with the task. The inherent risk an individual perceives in a given situation can provide more insight to an individual’s behavior (Stuck & Walker, 2019), which can be significant for understanding an individual's decision to rely on AI decision aids. Furthermore, research address that the domain that the risk is involved with can impact the perception of risk (Fox-Glassman & Weber, 2016; Wildavsky & Dake, 1990) and that some domains of risk may be more salient than others depending on the individual (Stuck et al., 2021).

The cultural concept of digital mindset is relatively new. It has become apparent in the later years, and the engagement in digital transformation initiatives is likely influenced by the individual's digital thinking and beliefs in technological change (Solberg et al., 2020). Building on implicit theories of intelligence, it describes an individual's beliefs about the malleability of their own technological abilities. As certain risk factors that are inherent in a situation can be more salient depending on the individual, there is reason to assume that an individual's digital mindset beliefs can influence the perception of risk. In turn, this can affect the individual's decision to rely on the AI decision aid. It is predicted that work performance in organizational settings will increasingly require cooperation with AI technology (Glikson & Woolley, 2020), and it is, therefore, evident to understand what influences individuals' decisions to rely on AI decision aid tools.

1.2 Research Question

As there is an increasing interest in using AI decision aid tools in organizational settings, our study aims to understand which domains of perceived situational risk to be the most important in influencing individuals' decision to rely on AI decision aids. To our knowledge, no other research has attempted to determine this. Additionally, we incorporate the concept of digital mindset to assess if certain risk factors present in a situation will be more noticeable for the individuals based on their digital mindset beliefs. Therefore, our research question is as follows:

"Does perceived situational risk influence an individual's decision to rely on AI decision aids, and will digital mindset make the risk factors inherent in the situation more salient?"

2.0 Literature Review

2.1 Artificial Intelligence and Artificially Intelligent Decision Aids

In the last few decades, developments of AI have rapidly increased, and scholars predict a future where individuals at work will cooperate with AI-embedded programs to assist in the process of organizational decision-making tasks (Metcalf et al., 2019; Shrestha et al., 2019). AI represents a new generation of technology which is highly complex and capable of interacting with the environment that aims to simulate human intelligence (Glikson & Woolley, 2020). The term "artificial intelligence" was first coined by John McCarthy in the 1950's and presented as "the science and engineering of making intelligent machines, especially intelligent computer programs" (McCarthy, 2007, p. 2). Today, AI is described as a technology that can collect and interpret data to perform cognitive tasks and generate solutions, decisions, and instructions (Glikson & Woolley, 2020). AI consists of a broad collection of computer-assisted systems for task performance (von Krogh, 2018) which differs from more traditional technology. However, the technical and specific details of AI are beyond the scope of this thesis.

AI can be embedded within different types of technology that have a diverse variety of functions. In this thesis, we concentrate on AI decision aids, which are computer programs where AI is used to make decision alternatives or recommended procedures to reach a specific goal (Shrestha et al., 2019; von Krogh, 2018). An example of an AI decision aid in a work-related setting is how corporate recruiters work with AI decision aids that collect and analyze information from job applicants to identify candidates with high potential (Solberg et al., 2022). Within organizations, the aid can offer benefits for decision-making, such as assisting employees with information processing (Shrestha et al., 2021). This can enhance analytical capabilities and possibly support the employees' transition towards more creative work. Furthermore, by working with AI decision aids, it is anticipated that task outcomes are performed more efficiently (von Krogh, 2018), which gives room for the employees to engage in other tasks at work.

There is a growing interest in implementing AI decision aid technology in organizations. Still, the success of integrating and working with AI is highly dependent on the employee's trust in such technology (Glikson & Woolley, 2020). There is an underlying and often problematic shift of authority when working with AI decision aids (von Krogh, 2018), as while the technology can make a decision, the individual is ultimately still responsible for the decision outcomes (Shrestha et al., 2019). Since it is predicted that work performance will increasingly require cooperation with AI and AI decision aids, it is crucial to understand what facilitates employees' choice to trust in and rely on AI (Glikson & Woolley, 2020).

2.2 Trust in and Reliance on AI Decision Aids

2.2.1 Mayer et al.'s Model of Trust

Organizational studies have for a long time emphasized the importance of trust as an essential component of interdependent working relationships (Colquitt et al., 2007; De Jong et al., 2016). In organizational settings, the most widely cited model of trust is Mayer, Davis, and Schoorman's (1995) integrated model of trust. In the model, trust is defined as

> *the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party.* (Mayer et al., 1995, p. 712)

This definition implies that there is a degree of risk involved when one is willing to be vulnerable by giving up control to allow another actor, the trustee, to perform a particular action that is important to the trustor. It suggests that trust does not signify taking risk but rather a willingness to take risk. Therefore, trust is evident when a trustor is willing to give control of an important action to another party, despite perceiving a risk when doing so associated with the uncertainty of the trustee's behavior (Mayer & Davis, 1999). Research on trust in organizational studies tends to focus on understanding risk and cooperation in interpersonal working relationships. Yet, researchers address the importance of trust when working with technology to create effective relationships (Hancock et al., 2011), especially AI-embedded technology that can facilitate organizational decision-making tasks (Glikson & Woolley, 2020). The trust that an individual develops towards AI technology will be fundamental to establishing the role of the technology in organizations progressing forward (Glikson & Woolley, 2020).

Mayer et al.'s (1995) definition of trust was originally developed for, but not limited to, human-human interaction in organizational settings. The emphasis on a willingness to be vulnerable, the importance of the actions at stake, and the potential for negative outcomes in their definition let us acknowledge trust in relation to technology, which also includes AI (Wang et al., 2016). However, research on trust in AI decision aids is broad, and several descriptions of trust have been defined in the literature. Still, in research where trust in AI decision aids or other related technology is defined, the definition of Mayer et al. (1995) is often applied and accepted because trust is not specified as only being limited to interpersonal relationships (Glikson & Woolley, 2020). Similarly, Solberg et al. (2022) elaborate and specify Mayer et al.'s (1995) model of trust in organizations and apply this to the context of human-AI decision aid work relationships. Therefore, we believe it is appropriate to use Mayer et al.'s (1995) model of trust moving forward in this thesis. However, there are some key elements in Mayer et al.'s (1995) model that we do not focus on, so we will therefore refrain from discussing some of these in relation to the description of human-AI decision aid relationship.

2.2.2 Perceived Risk

The focus on the aspects of a willingness to be vulnerable, the importance of the actions at stake, and the potential for negative outcomes in Mayer et al.'s (1995) model indicates the significance of understanding the concept of risk in relation to trust, as trust reflects the willingness to put oneself at risk. In their model, perceived risk is a central component. Perceived risk targets the individual's perception of risk, not an actual risk or hazard present in the context. It is about the psychological element of the risk, the individual's beliefs about risk, which will impact their trust and behavior. The construct has for some time been considered a single factor but Stuck et al. (2019) later identified subtypes of risk that are important and relevant to trust. These include perceived situational risk and perceived relational risk.

2.2.2.1 Perceived Situational Risk and Perceived Relational Risk

Perceived situational risk is described as an individual's beliefs about the likelihood and/or feeling that a specific task or context has potential negative outcomes due to the individual's experience and knowledge of the task (Stuck et al., 2019). This is regardless of the individual's knowledge or personal history of the trustee that might be relied on in the specific situation. This can also apply to the perceived risk of losing valued job resources, such as future career opportunities or job control, due to increasingly more work being allocated to AI rather than human beings (Glikson & Woolley, 2020; Solberg et al., 2020). It is about the risk rooted in the situation, which decides to rely on the trustee significant. For example, a corporate recruiter has been tasked with finding a new colleague for the recruitment team. Although the recruiter works with screening applications for the corporation daily, this new employee will be working closely with the recruiter and the team. Unconcerned with the recruiter's previous experience with the AI decision aid, the recruiter may perceive a higher situational risk by relying on the technology given the situation of how this new employee will directly impact the recruiter and the team specifically. The individual's trust in the AI decision aid must exceed their perceived situational risk for the individual to take a risk due to their trust (Stuck et al., 2019).

On the contrary, perceived relational risk refers to an individual's belief about the likelihood and/or feeling that interacting with another party has potential negative outcomes due to the individual's personal history or historical knowledge of the other party (Stuck et al., 2019). It is about the risk associated with the trustee not performing well, driven by the individual's experience, history, or relationship with the trustee (Stuck et al., 2019). There is also a likelihood of the individual contemplating the consequences if the AI performed poorly or inadequately and the perceived risk of being responsible for those consequences (Dwivedi et al., 2019). For example, the corporate recruiter using an AI decision aid to collect and analyze information from job applicants, could perceive a higher relational risk if the recruiter had previous experience with the aid not working properly (i.e., disregarding valuable information in some applications, thus overlooking applicants with high potential). The more risk associated with the AI decision aid, the less trust the individual will have in the trustee (Stuck et al., 2019).

As trust is relative to an uncertainty, the perceptions of risk are crucial in developing trust in technology (Hoff & Bashir, 2015). Trust affects what decisions an individual makes in risky or uncertain environments (Park et al., 2008). Thus, the level of trust between a human and AI would be severely critical in high-risk situations or high-performance environments (Groom & Nass, 2007; Schaefer et al., 2016). In Mayer et al.'s (1995) model, they intentionally separated the perceived risk related to the possibility of another party, the trustee, performing poorly or failing from the perceived risk associated with the chance of loss or disappointing outcomes in a situation which in return would make the decision to trust important and uncertain. In their model, perceived risk refers to "the trustor's beliefs about likelihoods of gains or losses *outside of considerations that involve the relationship with the particular trustee*" (Mayer et al., 1995, p. 726). Thus, the definition in their model reflects perceived situational risk. Moreover, in line with Mayer et al.'s (1995) model, perceived situational risk had been recognized as a crucial element in research on trust in automated and AI-embedded systems (Glikson & Woolley, 2020; Hoff & Bashir, 2015). As we intend to use Mayer et al.'s (1995) model of trust in our thesis, we will therefore only focus on perceived situational risk moving forward.

2.2.3 Reliance on AI Decision Aids

Trust can anticipate the level of reliance on technology (Glikson & Woolley, 2020), and research suggests that individuals reduce their reliance on technology when the risk is greater (Ezer et al., 2008; Rajaonah et al., 2008). The predicted outcome of Mayer et al.'s (1995) model involves risk-taking in the relationship and refers to "the behavioral manifestation of the willingness to be vulnerable" (i.e., trust) (p. 724), which is presented when the individual allows the other party to carry out an important task or action. Nevertheless, risk-taking in the relationship is not recognized as a behavioral presentation of trust in the model. Instead, it is viewed as the outcome of the interaction amid trust and the perceived situational risk. Based on this interaction, it is about the decision to rely on the trustee. Correspondingly in research on automation, the decision to rely on the technology is often presented as the behavioral outcome of trust (Lee & See, 2004), as the act reflects the individual allowing the technology to perform a task that is important to the trustor. In the context of AI decision aids, Solberg et al. (2022) argue that reliance is evident when an individual allows the AI decision aid to perform the decision-making task it is intended to do. The presence and growth of trust and the factors contributing to it can have effective and long-lasting effects in explaining the future behavior of individuals cooperating with such technology (Hancock et al., 2011).

2.3 Risk domains

Beyond the subtypes of perceived risk discussed above, there are also domains of risk that should be considered regarding the interaction between trust and perceived risk. Research addresses that the domain of which the risk is involved in can impact the perception of risk (Fox-Glassman & Weber, 2016; Wildavsky &

Dake, 1990), as the potential effect of risk is regulated by the degree of importance in the situation (Koller, 1988).

Jacoby and Kaplan (1972) presented a study where these domains of risk from consumer behavior literature were identified and tried to determine their interrelationships and uncover their individual and collective connection to overall perceived risk. From their study, five domains of perceived risk emerged. Moreover, these domains were functionally independent, implying that if one type of risk variety increased, another could either increase, decrease, or remain unchanged (Jacoby & Kaplan, 1972).

Concerning consumer behavior, Jacoby and Kaplan (1972) defined perceived financial risk as the possibility of losing money by trying a product from an unfamiliar brand. The second domain, perceived performance risk, described the likelihood of it being something wrong with a product from an unfamiliar brand or that it would not properly work. Third, perceived physical risk was defined as the possibility of a product from an unfamiliar brand could cause harm or injure the consumer by not being safe. The fourth domain, perceived psychological risk, refers to how a consumer's self-image or how he or she thinks about themselves would not fit well by trying a product from an unfamiliar brand. The last domain, perceived social risk, defined the chances of how a product of an unfamiliar brand would impact the way others think of the consumer. Lastly, overall perceived risk was described as how risky it would be to buy a product of an unfamiliar brand, considering all kinds of factors combined (Jacoby & Kaplan, 1972). While Jacoby and Kaplan (1972) conducted their study of these domains, Roselius (1971) identified time loss as a sixth domain of risk, which was defined as how one wasted time, convenience, and effort by getting a product repaired, adjusted, or replaced if the product failed.

Expanding the work of Jacoby and Kaplan (1972), Stuck and Walker (2019) investigated these domains of perceived risk concerning common or everyday technologies. They emphasized that there was a need not only to understand the overall perceived risk but also the domains of perceived risk, as the domains could have different impacts on overall perceived risk. Further, they argued that understanding the specific domain of perceived risk could provide more insight into which components of risk would have the most impact (Stuck & Walker, 2019). Their study demonstrates how even among common technologies, the types of risk will vary greatly for different technologies and in relation to overall perceived risk.

It concludes that perceptions of risks are fundamental to understand when gaining insight to individuals' behavior (Stuck & Walker, 2019).

2.3.1 Domains of Situational Risk in the Context of using AI Decision Aids

Stuck et al. (2021) then applied the domains of perceived risk uncovered from the work of Jacoby and Kaplan (1972) and Roselius (1971), among other domains, to the context of human-robot interactions. The domains are applicable to both perceived situational risk and perceived relational risk and Stuck et al. (2021) further described the domains in relation to these subtypes of risk. Solberg et al. (2022) took this a step forward and adapted the framework of Stuck et al. (2021) in relation to AI decision aids, where they defined and exemplified each domain of perceived situational risk within human-AI decision aid work relationships.

In their review, financial risk is described as the belief that an individual could lose money if the individual led AI decision aids to administer important tasks. Historically, this domain of risk is often connected to gambling but is applicable in any situation where there is a chance of losing money, such as handling expensive technology (Stuck et al., 2021). Solberg et al. (2022) exemplify how an employee believes she will lose her financial security due to losing her job if she lets AI decision aids carry out key parts of her work tasks.

Performance risk refers to the belief of how relying on AI decision aids could result in negative performance implications. Solberg et al. (2022) exemplify this as how a credit risk manager believes using an AI decision aid to perform customer risk assessments will cause issues for the customers, as they expect personal attention towards their personal assessment.

Physical risk was described as the belief that relying on AI decision aid could cause damage, lead to physical harm, or negatively impact health. An example is that by relying on an AI decision aid that prioritizes targets, an air defense system operator believes it could lead to errors with potentially damaging results as the aid reduces his situational awareness of the airspace (Solberg et al., 2022).

Psychological risk refers to the belief that it does not align with an individual's identity or could lead to negative psychological states (i.e., depression or anxiety) by relying on AI decision aids. Solberg et al. (2022) exemplify this situational risk by describing a manager who believes using an AI decision aid will remove intriguing work, which will reduce the job satisfaction he currently experiences.

Beyond an individual's self-image, social risk was described as the belief that relying on AI decision aids could affect how others think of the individual. An example of social risk is a doctor perceiving that the patients will undermine the doctor's expertise and credibility by using an AI decision aid to help diagnose the patients (Solberg et al., 2022).

Lastly, time loss risk is described as the belief of how one would use time ineffectively and inefficiently by relying on AI to perform a certain task. An example is an architect who believes it is a waste of time to collect and enter parameters an AI decision aid needs to produce building configurations as the architect and his colleagues already have some good ideas (Solberg et al., 2022).

While the domain of which the risk is involved in can influence the perception of risk (Fox-Glassman & Weber, 2016; Wildavsky & Dake, 1990), it should also be important to remark that some domains of risk may be more salient than others depending on the individual (Stuck et al., 2021). Even in situations where all domains described above are present, they may not all be equally salient to the individual, as individual factors contribute to the perception of risk experienced.

2.4 Digital Mindset: Fixed and Growth

2.4.1 Digital Transformation and Digital Mindset

Technology has become essential to success for many contemporary businesses today (Kane et al., 2017). The push towards a more digital transformation is driven by the belief that the technologies have the potential to provide more innovative and competitive advantages. Yet, the success of this transformation is rather dependent on the extent to which employees adopt the technology by accepting and using it (Legris et al., 2003). In the context of digital transformation, the term "digital mindset" has been extensively used by practitioners in the later years, claiming it is vital to have a digital mindset to succeed in a digitized workplace (Kane et al., 2017; Lipman, 2017). In general, it is understood as an organizational culture that highlights the influence of digital transformation and supports it in multiple ways (Solberg et al., 2020). Digital mindset has been conceptualized to include the aspect of "individual beliefs about the extent to which one's personal ability to learn and use new technologies are fixed or malleable" (Solberg et al., 2020, p. 3). They emphasize employees' beliefs in technological change and "digital thinking", which are likely to influence employees' engagement in digital transformation initiatives, whether to engage with or withdraw from it (Solberg et al., 2020).

2.4.2 Implicit Theories of Mindset

The implicit theories of intelligence describe assumptions about the nature and adaptability of individuals' personal attributes and influence how individuals make judgments, inferences, and reactions (Dweck et al., 1995). Research distinguishes between two implicit theories, referred to entity theory and incremental theory (Dweck, 1986). Entity theory describes the beliefs of attributes, such as intellectual abilities, being trait-like entities that cannot develop or improve. These are static. Incremental theory concern beliefs about how attributes are dynamic and developable. These can be learned and improved through effort over time, thereby, it is malleable (Dweck et al., 1995). Later, these theories were coined as fixed and growth mindsets (Dweck, 1986). Fixed mindset is defined as the belief of personal attributes being constant or static (entity theory), whereas growth mindset refers to the belief of personal attributes being developed and enhanced over time through effort (incremental theory) (Dweck, 2006). When encountering an event that is negatively loaded, such as a situation that feels challenging to overcome, those who have a fixed mindset and those who have a growth mindset will respond differently (Dweck et al., 1995).

2.4.3 Fixed Mindset

Individuals with a fixed mindset tend to look for situations where their intelligence, abilities, or competence can be validated (Dweck & Leggett, 1988). Thus, they tend to avoid situations where they could be perceived as incompetent. Similarly, they are more prone to turn down help from others and rarely seek help as it could label them as being incompetent (Dweck & Yeager, 2019). In relation to the workplace, an employee with a fixed mindset and beliefs of how one's own skills, strengths, and abilities cannot improve may tend not to develop within the workplace to the same degree as other employees (Han & Stieha, 2020). This can be explained by how these employees tend to choose work tasks they are familiar with and know how to perform rather than exploring new tasks where they will have an opportunity to develop their attributes. When faced with obstacles or challenges, research shows that individuals with a fixed mindset will reduce their effort or remove themselves from the situation (Dweck & Leggett, 1988). For individuals with a fixed mindset, everything is about the outcome (Dweck, 2017). Thus, if one were to fail, or not be the best, the work leading up to the outcome is considered a waste.

2.4.4. Growth Mindset

On the contrary, individuals with a growth mindset are more likely to look for situations where they can increase their intelligence, abilities, or competencies (Dweck & Legget, 1988). When encountering challenges or obstacles, individuals with a growth mindset tend to approach the situation with more effort and thus, learn new skills. Conversely to individuals with fixed mindset, those with a growth mindset tend to seek help and use this to achieve new learning goals (Dweck & Yeager, 2019). In relation to the workplace, employees with a growth mindset tend to embrace situations where they try new work tasks and further develop their human attributes (Han & Stieha, 2020). Research suggests that employees with a growth mindset positively impact individual- and organizational performance due to their development and improvement of human attributes (Han & Stieha, 2020). Furthermore, it is emphasized that individuals with a growth mindset often tend to be more open to changes, such as using a new type of program or solutions in the workplace. For individuals with a growth mindset, it is about being able to value what they are doing, regardless of the outcome (Dweck, 2017).

However, it is essential to note that there is no right or wrong between the two mindsets, but instead that they refer to how different reality is viewed. Further, it is essential to emphasize that an individual often holds a mixture of the two mindsets (Dweck, 2015) and therefore does not exclude one from the other. An individual may react or make judgments with a fixed mindset in a given situation and with a growth mindset in another.

2.4.5 Fixed Digital Mindset and Growth Digital Mindset

In this thesis, we chose to conceptualize digital mindset based on the work of Dweck's (2017) characterization of fixed and growth mindset. In present research, digital mindset is described as an individual's beliefs towards the malleability of their own technological abilities (Solberg et al., 2020). Depending on whether these abilities are fixed or malleable, they will influence how individuals make judgments, inferences, and reactions differently in relation to digital transformation and technological change (Solberg et al., 2020). As mindsets can have a dominant effect on an individual's feelings, cognitions, and behavior (Kray & Haselhuhn, 2007), we want to examine if an individual's fixed digital mindset (henceforth, FDM) or growth digital mindset (henceforth, GDM) will influence their decision of relying on an AI decision aid in an organizational setting.

We describe FDM as beliefs of personal technological abilities being unchangeable and static, whereas a GDM refers to beliefs that these technological abilities can develop and enhance through effort. An employee with a GDM may see the technology transformation initiatives as an opportunity to learn, thus being more willing to use the new technology and learn from it. In contrast, an employee with a FDM may perceive the new initiative as a possible threat towards looking incompetent as the new technology would need to be mastered, thereby avoiding it. The concept of digital mindset seeks to provide advice so employees in corporations can better understand and utilize digital thinking in technological change initiatives and address the implications of dealing with digital transformation (Solberg et al., 2020).

3.0 Theoretical Framework and Hypotheses

3.1 Perceived Situational Risk and the Decision to Rely on an AI Decision Aid

As previously addressed, the perceptions of risk are crucial to understanding the development of trust in technology (Hoff & Bashir, 2015), as trust can affect what decision an individual will act upon in given situations (Park et al., 2018). There have not been developed specific propositions in Mayer et al.'s (1995) model of how different levels of trust and perceived risk interact and how this interaction is displayed when the trustor allows the trustee to carry out a crucial task for the trustor. However, we can assume that there will be a less positive relationship between trust and making the decision to rely on the trustee if the perceived risk is high. It is essential to understand that without risk, there is no trust (Stuck et al., 2021). If the trustor perceives no risk, then the trustor does not necessarily need to trust the trustee to rely on it.

Stuck and Walker (2019) emphasized that to understand an individual's behavior towards their perception of risk it was essential to uncover which domains of risk that were relevant in specific situations. In their study, they concluded that on the different domains of risk, technological work-related devices such as smartphones or laptop computers scored highest on performance-, social-, and psychological risk. In relation to the decision of relying on an AI decision aid to carry out a decision-making task, Solberg et al. (2022) assume that perceived performance situational risk could be a vital domain as individuals could believe relying on an AI decision would negatively impact their own performance. Similarly, perceived psychological situational risk could also be an essential domain as individuals could believe that relying on an AI decision aid will result in reduced job satisfaction or loss of task identity (Solberg et al., 2020). Furthermore, in an organizational setting, we assume that perceived social situational risk could be an important domain as individuals could believe that other employees would undermine their credibility by relying on an AI decision to carry out a critical decision-making task for them.

Based on the findings from Stuck and Walker (2019) and the beliefs of Solberg et al. (2022), as well as our assumptions, we, therefore, chose to focus on performance-, social-, and psychological risk as the main domains of perceived situational risk to explain an employee's behavior of relying on AI decisions aids at work. Therefore, our hypothesis is as follows:

> *H1: There will be a negative relationship between perceived performance-, social-, psychological situational risk and the decision to rely on the AI decision aid.*

3.2 Digital Mindset, Perceived Situational Risk, and the Decision to Rely on an AI Decision Aid

Stuck et al. (2021) argue that some domains of risk may be more salient than others in a given situation as the perception of risk is dependent on individual factors. Therefore, we believe that an individual's digital mindset beliefs will make certain risk factors that are inherent in a situation more salient. Solberg et al. (2022) define perceived performance situational risk as the belief that relying on AI decisions could result in negative performance implications. However, the failure to deliver the desired performance does not concern performance deficiencies of the AI decision aid. As an individual with a fixed mindset prefers tasks they are familiar with and know they can master (Dweck, 2006), we propose that the perceived performance risk of relying on an AI decision to carry out a task for them without knowing the outcome in the situation will be greater for those with a FDM compared to those with a GDM. If the outcome is negative, an individual with a FDM can view this as a failure, thus inflicting on their performance. On the contrary, individuals with a GDM tend to embrace challenges. They may therefore see this as an opportunity to learn, regardless of the outcome, thus not perceiving a high performance risk in this situation.

Further, individuals with a fixed mindset tend to avoid situations where they can be perceived as incompetent by others (Dweck & Leggett, 1988). Solberg et al. (2022) define perceived social situational risk as the belief that relying on AI decision aids could affect how others think of the individual. We, therefore, propose that individuals with a FDM will perceive higher social risk in situations where they rely on the AI decision aid to perform the task for them, compared to those with a GDM, as they are afraid to be perceived as incompetent by others because they did not do the task themselves.

Moreover, Solberg et al. (2022) describe perceived psychological situational risk as the belief that relying on AI decision aid is not in line with the individual’s identity or that it could lead to negative psychological states. As individuals with a fixed mindset tend to seek situations where their abilities can be validated (Dweck & Leggett, 1988), we propose that individuals with a FDM will perceive the psychological risk to be more salient in situations where they rely on the AI decision aid to perform the task for them, as their abilities cannot be validated to the same extent because they did not do the task themselves. Conversely, we believe that those with a GDM will perceive a low psychological risk, as relying on an AI decision aid can provide opportunities to reach new learning goals. With this in mind, we propose the following hypothesis:

> *H2: Individuals having a high (versus low) FDM will perceive greater a) performance-, b) social-, c) psychological risk in situations requiring the decision to rely on AI decision aid. In turn, the decision to rely on the AI decision aid will be significantly lower when an individual’s FDM is high (versus low).*

4.0 Research Method

4.1 Research Design

To answer our research question in the best possible way, we believe that quantitative research with an experimental vignette design is the most suitable, as the quantitative research design stresses quantification within the collection and analysis of the data. In addition, it is often more deductive and objective and incorporates a more natural science model of the research process (Bell et al., 2019). In experimental vignette design, the participants are presented with specific, carefully planned scenarios that assess the dependent variables and their intentions, attitudes, and behaviors. Further, by using an experimental vignette design, experimental realism intensifies because the researchers have the opportunity to manipulate and control the independent variables. This helps increase internal and external validity (Atzmüller & Steiner, 2010; Hox et al., 1991).

According to Cavanaugh and Fritzsche (1985), this method is particularly useful when those who carry out the study want control over the independent variables. They stress that one wants this control to obtain evidence between cause and effect. Further, this type of experiment benefits the research by including the factors most relevant to the research question while excluding those that will confuse the result. This process and control assist in testing causal hypotheses to a greater extent, which can usually be difficult to test. The design is especially useful when there is a need to determine the direction of the causal relationship (Aguinis & Bradley, 2014).

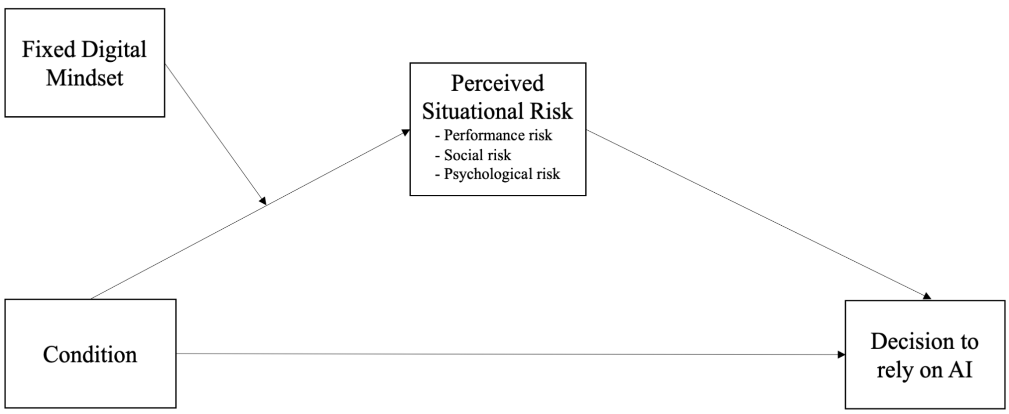
To strengthen the quality of our research, reliability and validity are criteria that are crucial to consider. Reliability concerns the consistency of measures, whereas validity refers to whether a measure of a concept really measures that concept (Bell et al., 2019). A strength of experimental vignette design is that the internal validity is high since the external validity is sacrificed (Argyris, 1975; Scandura & Williams, 2000). Although external validity is often lower in experimental vignette design, it is possible to increase the external validity. This can, for example, be done by providing the participants with greater in-depth knowledge of the scenarios they are being presented with since they are often approaching the real world (Heslin et al., 2006). With this in mind, we wanted to ensure that the participants were presented with as realistic vignette scenarios as possible with enough relevant information to increase the realism level in our study.

In this study, we conducted a survey (see appendix 1 for all survey questions) to collect data on FDM (the moderator), Perceived Situational Risk (the mediator), Perceived Situational Risk Conditions (the independent variables), and Decision to Rely on AI (the dependent variable) of our model. The different variables are depicted in our research model (Figure 1) below, which is applied to address our research question. In the first part of the survey, we determined the participant's digital mindset using an adapted scale from Levy et al. (1998). We will return to describe this further below. Then, the participants were presented with one out of four different vignette scenarios, all of which consisted of different conditions. In our scenarios, we created a hypothetical case where the respondent had to decide whether or not they were willing to rely on an ERP-system that would calculate bonuses for employees automatically. The vignettes were identical in all experimental conditions except for the parts that contained experimental manipulations. The first scenario was the control scenario, which only contained standard text and no experimental manipulation. The second scenario contained a manipulation that was intended to trigger performance risk. In the third scenario, we added a manipulation intended to trigger social risk. Lastly, the fourth scenario consisted of a manipulation intended to trigger psychological risk. Participants were randomly exposed to one of the four scenarios regardless of what they had answered in previous questions.

4.1.1 Research Model

Our research model (Figure 1) is inspired by Mayer' et al. 's (1995) model of organizational trust, and we use this to integrate, compare, analyze, and organize research of perceived situational risk, FDM, and the decision to rely on AI.

Figure 1. Research model



4.2 Sample and Procedure

In this study, non-probability sampling has been conducted using the snowball effect as we used our social network to collect the relevant primary data by publishing the survey on Facebook and LinkedIn. Non-probability sampling is a method of sampling where a random way of collecting the data is not being conducted which further implies that some part of the population is, therefore, more likely to be selected than others (Bell et al. 2019). Furthermore, since our network consists primarily of Norwegian and English speakers, we distributed the survey in both Norwegian and English.

Regarding sampling, it is also relevant to examine the sample size. When deciding the sample size, it is often dependent and affected by time and cost considerations. Furthermore, it is essential to focus on the total size rather than the relative size of the sample (Bell et al., 2019). In this research, our goal was to receive approximately 200 respondents. At the same time, it was vital to consider that there may be some non-respondents. Therefore, it was crucial to obtain a few more respondents than 200. When the data collection ended, we had gathered a total of 250 respondents. Then, we cleaned the data set and removed the respondents who used exceptionally long or short time answering the survey and those who did not complete it. In the end, the final data set consisted of 192 respondents, which provided us with approximately 50 respondents for each vignette scenario.

Based on the participants that answered the survey, 77 (40.1%) were male, 114 (59.4%) were female, and 1 (0.5%) did not wish to answer. For age, 1 (.5%) were under 20, 74 (38,5%) between 20-29 years, 36 (18,8%) were between 30-39 years, 26 (13,5%) were between 40-49 years, 32 (16,7%) were between 50-59 years, 20 (10,4%) were between 60-69 years and 3 (1,6%) were above 70 years. 24 participants had experience with calculating bonuses manually, 10 participants had experience with calculating it through ERP-system or similar, and 160 participants had no experience calculating bonuses.

4.3 Measures

In this thesis, we used the Likert scale on most of the questions to collect the data, where the respondents selected how much they agreed or disagreed with the statements presented (see appendix 1 for all measures).

4.3.1 FDM and GDM

When measuring the respondent's digital mindset beliefs, we took inspiration from the scale used by Levy et al. (1998), which measures whether an individual has a fixed or growth mindset. As a part of the survey, we adapted this scale by adding "technological skills/abilities" in relation to digital mindset. An example of a question from Levy et al. (1998) to measure this is "everyone is a certain kind of person, and there is not much that they can do to really change that." Similar statements were adapted regarding how a mindset could influence relying on AI. Participants scoring high on this scale implied they had more of a FDM, whereas participants scoring low implied they had more of a GDM.

4.3.2 Perceived Performance-, Social-, and Psychological Situational Risk

When we measured the mediated variables of perceived situational risk with the domains of performance-, social-, and psychological risk, we adapted the measure created by Jacoby & Kaplan (1972). This measure was a part of the vignette scenarios where the participants had to answer what kind of risk they perceived when presented with one of the different scenarios. As Jacoby and Kaplan's (1972) measure was originally used to measure perceived risk in relation to consumer behavior, we adapted this to apply to AI decision aids technology.

Even though we only focused on measuring three of Jacoby & Kaplan´s (1972) perceived risks in our study, we made all six domains of risk available for the participants to select between. This was done to ensure that we were testing what we were supposed to test and to examine if the participants perceived the intended situational risk we are suggesting in our hypothesis. For example, in the study of Jacoby and Kaplan (1972) perceived performance risk was measured as "what is the likelihood that there will be something wrong with an unfamiliar brand of ____or that it will not work properly?" (p. 11). In our study, similar statements were adapted to measure perceived situational risk in relation to AI decision aids that were relevant for our research.

4.3.3 Decision to Rely on AI

The last variable in our model is the dependent variable Decision to Rely on AI. Again, it is not reliance that is being measured, but the *intention to rely.* The respondents had to make a decision of whether they intended to rely on the AI decision aid, in this case, the ERP-system, based on the information they received from one of the four different vignette scenarios they were presented with. To measure this, the respondent would rate on the Likert scale to what extent they experienced any perceived situational risk and if they intended to rely on the system to perform the task for them or not.

4.4 Research Ethics

The ethical aspect is an essential part of the study that must be valued when collecting data. Further, the study needs to continuously revisit the ethical considerations throughout (Bell et al., 2019). In connection with this study, we started by examining the ethical guidelines and rules to ensure that we followed the ethical guidelines required by law when obtaining data. When creating the survey, we did not send our survey to NSD (Norwegian Center for Research Data) regarding personal data and data collection for approval since we did not collect personal or sensitive information from the participants. Furthermore, the survey was designed so that the overall combination of information cannot be linked to a person or other personal information.

Regarding this thesis, we discovered some ethical principles which were highly important to shed light on. Firstly, it was necessary for us that those who participated in the survey received all the information they needed to be able to answer the survey or make the decision of whether to participate or not. This refers to the principle of informed consent (Bell et al., 2019). In addition, we found it vital to focus on the anonymity of the participants in the study. Being anonymous when responding to a survey can be necessary for participants, and it was something we wanted to ensure.

In the following two sections (5.0 Analysis and 6.0 Results), we abbreviate the variables described in our model for brevity’s sake. For example, when discussing Perceived Performance Risk, we will refer to this as PPR.

5.0 Analysis

5.1 Scale Reliability

The analysis in this thesis was carried out step by step. First, as a part of the descriptive analysis, it was essential to conduct a reliability analysis. In this context, we conducted a reliability analysis to examine the internal reliability of the respondent’s digital mindset. It essentially calculates the average of all possible split-half reliability coefficients. As a rule of thumb, .70 is said to be a computed acceptable Cronbach’s alpha coefficient (Bell et al., 2019). In the reliability analysis, we added all the questions concerning digital mindset to the analysis. We also reversed one of the questions since it is primed differently and in the opposite direction than the other questions that measure the participants' FDM.

5.2 Hypothesis Testing

Further, in the next step of the analysis, we did a correlation analysis, which is a statistical measure of how much two measurable quantities are related to each other. On hypothesis 1, we did a Pearson's correlation analysis which is a coefficient of test statistics that measures the statistical relationship, or association, between two continuous variables. This analysis is acknowledged as a good tool for measuring the relationship between variables of interest because it is based on the covariance method (Bell et al., 2019). Here, we compared the connection between all the perceived situational risks and the decision to rely on AI.

To test hypothesis 2a, 2b, and 2c we used Process macro for SPSS (version 4.1) created by Andrew Hayes (Hayes, 2022), which enables simultaneous testing for the entire mediation and moderation model. At the same time, it also integrates bootstrapping techniques for estimating indirect effects, preferably used by methodologists instead of causal steps and Sobel test strategies (Baron & Kenny, 1986). The method of bootstrapping is where the data is repeated to establish confidence intervals for the indirect effect (Preacher & Hayes, 2008). If zero is not included in the interval range, one can argue that the effect of the independent variable on the dependent variable is mediated by the mediation variable. However, Sobel tests or other causal step strategies are recommended in other studies where the samples are larger (Preacher & Hayes, 2008). Further, the process macro test has a higher power. It keeps more control over Type I error, which refers to when a relationship between two variables is concluded when there is none (Banerjee et al., 2009).

Hypothesis 2a, 2b, and 2c were tested using PROCESS Model 7, which allows for the moderation (PROCESS Model 1) and mediation (PROCESS Model 4) effects to be tested simultaneously, which further provides the effects on the overall outcome. For hypothesis 2a, X = Condition: Performance Risk (CPR), Y = Decision to Rely on the AI Decision Aid (Rely), M = Perceived Performance Risk (PPR), and W = FDM. For hypothesis 2b, X = Condition: Social Risk (CSR), Y = Rely, M = Perceived Social Risk (PSR), and W = FDM. Lastly, for hypothesis 2c, X = Condition: Psychological Risk (CPSR), Y = Rely, M = Perceived Psychological Risk (PPSR), and W = FDM. The tests were conducted with a 95% confidence interval using bootstrapping with 10,000 resamplings.

6.0 Results

6.1 Scale Reliability

In the reliability analysis, we found that the FDM measure had acceptable internal reliability in the current sample since the Cronbach's alpha was .802.

6.2 Hypothesis Testing

6.2.1 Hypothesis 1

The results presented in Table 1 concern the testing for hypothesis 1. As shown in the table, perceived performance-, social-, and psychological situational risk were negatively related to the decision to rely on the AI decision aid, and all relationships were significant. Thus, hypothesis 1 is supported.

Table 1. Correlation analysis

Decision to rely on AI		Perceived performance risk	Perceived social risk	Perceived psychological risk	Perceived financial risk	Perceived physical risk	Perceived time loss risk	Overall perceived risk
	Person correlation	-.392**	-.219**	-.215**	-.222**	-.109	-.340**	-.479**
	Sig. (2-tailed)	<.001	.002	.003	.002	.132	<.001	<.001

*Note. N = 192. *p<.05, **<p<.01, ***p<.00.*

6.2.2 Hypothesis 2a

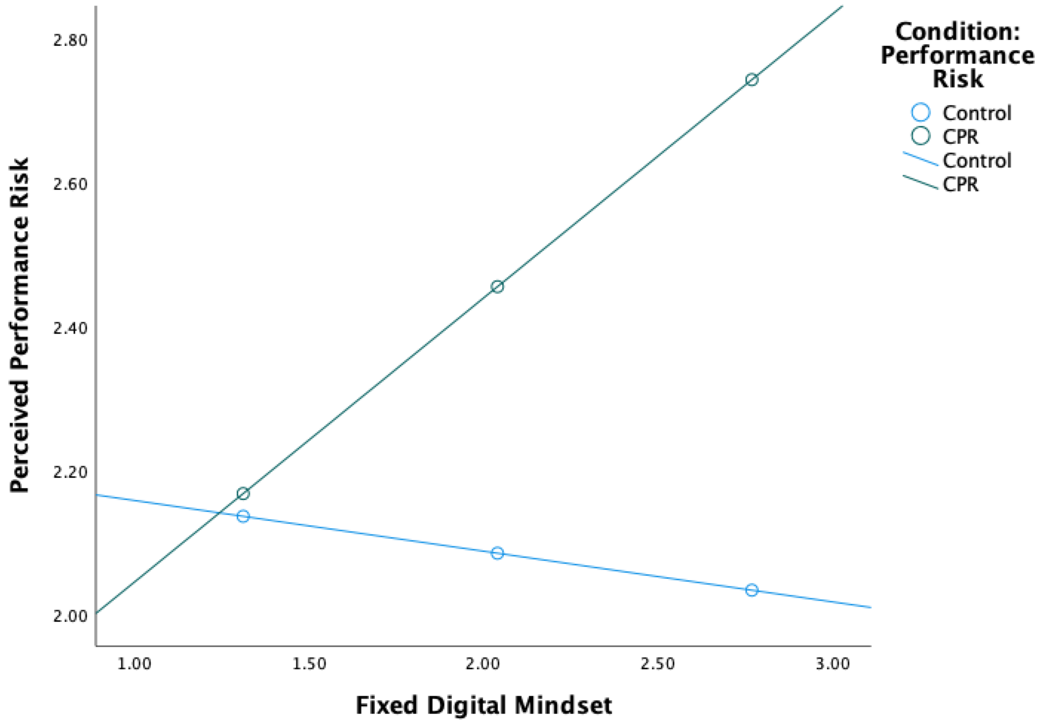
Table 2 represents the findings related to testing Hypothesis 2a when perceived situational risk is set to be performance risk. The main effect of CPR on PPR is negative but not significant ($b = -.58$, $t = -1.00$, 95% CI = -1.7196, .5648, $p = .32$). Nevertheless, the interaction effect between FDM and CPR is marginally significant ($b = .46$, $t = 1.73$, 95% CI = -.0672, .9961, $p = .08$). The low FDM level simple slope showed a non-significant relationship. The mean level was marginally significant, but the high FDM level simple slope increased the effect of CPR on PPR ($b = .71$, $t = 2.60$, 95 CI = .1677, 1.2499, $p<.05$). This is also illustrated in Figure 2, which shows that CPR is more positively related to PPR when FDM is high, implying that when FDM increases the perceived performance risk increases. This lends support to our hypothesis of how FDM moderates the relationship between CPR and PPR. This moderation was further noticed when the value of FDM continued to increase and how it positively related to PPR (See appendix 2).

Table 2: Moderation Effect of FDM on the Relationship between CPR and PPR

Perceived Performance Risk		*b*	*t*	CI95% *Lower*	CI95% *Upper*	*p*
Constant		2.80(.96)**	2.91	.8918	4.7194	.00
CPR		-.58(.57)	-1.00	-1.7196	.5648	.32
DM		-.54(.45)	-1.18	-1.4386	.3689	.24
CPR x FDM		.46(.27)	1.73	-.0672	.9961	.08
	(1)	.03(.27)	.12	-.5024	.5654	.91
	(2)	.37(.18)	1.97	-.0023	.7425	.05
	(3)	.71(.27)*	2.60	.1677	1.2499	.01

Note. N=93. b = unstandardized coefficient; CI95% = confidence interval.
**p <.05. **p <.01, ***p <. 001. Slopes (1): Low digital mindset, (2): Mean digital mindset, (3): High digital mindset. Standard Errors are in parentheses.*

Figure 2. Interaction between FDM, Condition: Control (CC) and CPR on PPR



Note. N=93.

Table 3 presents the results connected to testing the mediation effect of hypothesis 2a. These findings indicate that CPR is positively and significantly related to PPR (b = .38, t = 1.99, 95% CI = (.0013, .7610), p <.05). PPR is negatively and significantly related to Rely (b = -.50, t = -4.77, 95% CI = (-.7134, –.2940), p<.01). The test of the mediating effect of PPR between CPR and Rely showed a negative significant coefficient, as the confidence interval for the indirect effect did not include zero (b = -.04, SE = .20, t = -.22, 95% CI = -.3887, -.0017).

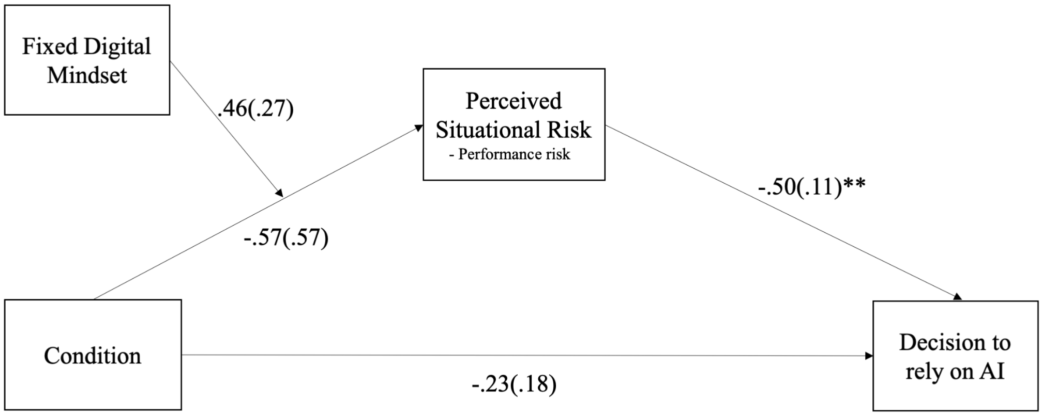
Table 3. Mediation Effects of PPR on the Relationship between CPR and Rely

	Perceived Performance Risk (M)					Decision to Rely on AI (Y)				
			$CI_{95\%}$					$CI_{95\%}$		
	b	*t*	*Lower*	*Upper*	*p*	*b*	*t*	*Lower*	*Upper*	*p*
Constant	1.71(.30)**	5.62	1.1033	2.3083	.00	5.14(.35)**	14.49	4.4333	5.8420	.00
CPR (X)	.38(.19)*	1.99	.0013	.7610	.049	-.04(.19)	-.22	-.4338	.3478	.83
PPR (M)						-.50(.11)**	-4.77	-.7134	-.2940	.00
Indirect Effect						-.19(.10)		-.3887	-.0017	
Direct Effect						-.04(.20)	-.22	-.4338	.3478	.83
Total Effect						-.24(.21)	-1.10	-.6607	.1908	.28

Note. N = 93. b = unstandardized coefficient; CI95% = confidence interval.
**p<.05, **p<.01, ***p<.00. Standard Errors are in parentheses.*

The analysis conducted to test Hypothesis 2a revealed a non-significant index of the moderated mediation effect of CPR on Reliance through PPR with FDM moderating the relationship between CPR and PPR (indirect effect = -.23; 95% CI = (-.6346, .0946) (the unstandardized coefficients for the different paths are represented in Figure 3). Further, the direct effect of CPR on Rely was not significant (b = .04, t = -.29, 95% CI = (-.4338, .3478), p = .82), and FDM did only serve a marginally significant moderator for this relationship (b = .46, t = 1.73, 95% CI = -.0672, .9961, p = .08). However, we noticed a significant and negative relationship between PPR and Rely (b = -.50, t = -4.77, 95% CI = (-.7134, -.2940). Hypothesis 2a is not supported, but there is a pattern existing between CPR and PPR when FDM increases, that further affects PPR and Rely, which is worth looking further into.

Figure 3: Moderated Mediation Model for CPR and Rely



*Note. N=93. Unstandardized coefficients with standard errors (in parentheses). *p<.05, **p<.01, ***p<.001.*

6.2.3 Hypothesis 2b

Table 4 represents the findings related to testing the moderation effect of Hypothesis 2b when perceived situational risk is set to be social risk. The main effect of CSR on PSR was not significant (b = -.30, t = -1.04, 95% CI = -.8744, .2732, p =.30). Neither was the interaction effect between FDM and CSR (b = .20, t = 1.42, 95% CI = -.0777, .4719), p = .16).

Table 4. Moderation Effect of FDM on the Relationship between CSR and PSR

			CI95%		
Perceived Social Risk	*b*	*t*	*Lower*	*Upper*	*p*
Constant	1.4(.65)*	2.15	.1089	2.6913	.03
CSR	-.30(.29)	-1.04	-.8744	.2732	.30
DM	.16(.31)	.53	-.4501	.7805	.59
CSR x FDM	.20(.14)	1.42	-.0777	.4719	.16

Note. N=96. b = unstandardized coefficient; CI95% = confidence interval.
**p <.05. **p <.01, ***p <. 001. Standard Errors are in parentheses.*

Table 5 illustrates the results in testing the mediation effect of hypothesis 2b. These findings indicate that CSR is positively related to PSR (b = .09, t = .94, 95% CI = -.0961, .2701), p = .35) but not significant. PSR is negatively and significantly related to Rely (b = -.26, t = -2.34, 95% CI = -.4739, -.0391), p = .02). However, the test for the mediating effect of PSR between CSR and Rely was not significant (b = -.02, SE = .03, 95% CI = (-.0909, .0247).

Table 5. Mediation Effects of PSR on the Relationship between CSR and Rely

	Perceived Social Risk (M)					Decision to Rely on AI (Y)				
			CI95%					CI95%		
	b	*t*	*Lower*	*Upper*	*p*	*b*	*t*	*Lower*	*Upper*	*p*
Constant	1.74(.21)**	8.30	1.3229	2.1553	.00	4.56(.29)**	15.58	3.9799	5.1428	.00
CSR (X)	.09(.09)	.94	-.0961	.2701	.35	-.05(.09)	-.50	-.2447	.1458	.62
PSR (M)						-.26(.11)*	-2.34	-.4739	-.0391	.02
Indirect Effect						-.02(.03)		-.0909	.0247	
Direct Effect						-.05(.10)	-.50	-.2447	.1458	.62
Total Effect						-.07(.10)	-.72	-.2707	.1272	.47

*Note. N = 96. b = unstandardized coefficient; CI95% = confidence interval. * p<.05, **p<.01, ***p<.00. Standard Errors are in parentheses.*

The findings related to the analysis conducted on Hypothesis 2b were not significant, with the index of the moderated mediation effect of CSR on Reliance on AI through PSR with FDM moderating the relationship between CSR and PSR (indirect effect = -.05; 95% CI = (-.1803, .0386)). Neither was the direct effect of C~~P~~SR on Reliance (b = -.05, t = -.50, 95% CI = (-.2447, .1458), p = .62). FDM did not show a significant moderation for this relationship (b = .20, t = 1.42, 95 CI = (-.0777, .4719), p = .16). Nevertheless, the same pattern occurred as in hypothesis 2a with a significant and negative relationship between PSR and Rely (b = -.26, t = -2.34, 95 CI = (-.4739, -.0391), p =.02). Still, hypothesis 2b is not supported.

6.2.4 Hypothesis 2c

Table 6 illustrates the findings from testing the moderation effect of hypothesis 2c where perceived situational risk is set to be psychological risk. The main effect of CPSR on PPSR was not significant (b = -.03, t = .20, 95% CI = (-.2876, 3538), p = .84). Neither was the interaction effect between FDM and CPSR (b = -.00, t = -.04, 95% CI = (-.1546, .1478), p = .96).

Table 6. Moderation Effect of FDM on the Relationship between CPSR and PPSR

			CI95%		
Perceived Psychological Risk	*b*	*t*	*Lower*	*Upper*	*p*
Constant	1.10(.51)*	2.17	.0935	2.1152	.03
CPSR	-.03(.16)	.20	-.2876	.3538	.84
DM	.27(.24)	1.12	-.2097	.7516	.26
CPSR x FDM	-.00(.07)	-.04	-.1546	.1478	.96

Note. N = 95. b = unstandardized coefficient; CI95% = confidence interval.
**p <.05. **p <.01, ***p <.001.*

Table 7 represents the findings for testing the mediation effect of hypothesis 2c. It indicates that CPSR is positively related to PPSR but not significant (b = .03, t = .51, 95% CI = -.0776, .1317), p = .61). PPSR was negatively and significantly related to Rely (b = -.35, t = -2.47, 95% CI = (-.6381, -.0692), p<.05). The test for the mediating effect of PPSR between CPSR and Rely was negative but not significant (b = -.01, SE = .02, 95% CI = (-.0533, .0339).

Table 7. Mediation Effects of PPSR on the Relationship between CPSR and Rely

	Perceived Psychological Risk (M)					Decision to Rely on AI (Y)				
			$CI_{95\%}$					$CI_{95\%}$		
	b	*t*	*Lower*	*Upper*	*p*	*b*	*t*	*Lower*	*Upper*	*p*
Constant	1.65(.15)**	10.57	1.3375	1.9562	.00	4.76(.32)**	14.90	4.1219	5.3901	.00
CPSR (X)	.03(.04)	.51	-.0776	.1317	.61	-.12(.07)	-1.65	-.2654	.0242	.10
PPSR (M)						-.35(.14)*	-2.47	-.6381	-.0692	.01
Indirect Effect						-.01(.02)		-.0533	.0339	
Direct Effect						-.12(.07)	-1.65	-.2654	.0242	.10
Total Effect						-.13(.07)	-1.74	-.2786	.0183	.08

Note. N = 95. b = unstandardized coefficient; CI95% = confidence interval.
**p<.05, **p<.01, ***p<.00. Standard Errors are in parentheses.*

The index of the moderated mediation effect of CPSR on Rely through PPSR with FDM moderating the relationship between CPSR and PPSR in hypothesis 2c was not significant (indirect effect = .00, 95% CI = (-.0712, .0636)). The direct effect of CPSR on Rely was also not significant (b = -.35, t = -1.65, 95% CI = (-.2654, .0242), p = .10), and FDM did not significantly moderate this relationship (b = -.00, t = -.04, 95% CI = -.1546, .1478), p = .96). However, we observed the same pattern again where there is a negative and significant relationship between PPSR and Rely (b = -.35, t = -2.47, 95% CI = (-.6381, -.0692), p = .02). Nevertheless, hypothesis 2c is not supported.

7.0 Discussion

The main purpose of this study was to examine how perceived situational risk, namely performance-, social-, and psychological risk would affect the decision to rely on AI decision aid used in the workplace. Further, we considered how an individual's mindset beliefs could make certain risk factors inherent in a situation more salient and how this could influence the decision to rely on an AI decision aid to perform a decision-making task.

7.1 Hypotheses

7.1.1 Hypothesis 1

In terms of our hypothesis concerning if there is a negative relationship between perceived performance-, social-, and psychological situational risk, and the decision to rely on an AI decision aid, we can confirm through the results of our analyzes that there is a significant negative relationship. Mayer et al. (1995) emphasize that there is some risk involved in interrelationships when an individual is willing to be vulnerable to trust another party to perform an action important to the trustor. Present research has taken this a step further and applied the model of Mayer et al. (1995) in relation to individuals trusting in and relying on AI technology and AI decision aids (e.g., Glikson & Woolley, 2020; Solberg et al., 2022). This aligns with our results being significant and can support the reason for it being a negative relationship between perceived situational risk and the decision to rely on the AI decision aid.

Furthermore, we wanted to investigate if a specific domain of perceived situational risk would impact an individual's decision to rely on an AI decision aid, as research stress that the perceptions of risk are vital in the development of trust (Hoff & Bashir, 2015). The greater the perceived risk, the less willing an individual might be in deciding to rely on an AI decision aid in the situation. As previously described, we applied several domains of perceived situational risk in relation to the decision of relying on the ERP-system. Except for perceived physical risk, all the domains were significant, including the three domains we proposed in our hypothesis. However, perceived performance risk was the most significant domain in our findings. These findings reflect Stuck & Walker's (2019) study where work-related devices such as smartphones or laptops scored high on perceived performance-, social-, and psychological risk.

Essentially, our findings have established that there is a negative correlation between the perceived performance-, social-, and psychological situational risks and the decision to rely on AI decision aids. Therefore, we will take this a step further in the following hypothesis by discussing this relationship.

7.1.2 Hypothesis 2

Although there was no significant support for hypothesis 2 (a, b, and c), there are still findings worth pursuing further. As previously addressed, the potential effect of risk is determined by the importance of the situation (Koller, 1988), which is why we wanted to gain more knowledge of how the different domains of perceived situational risk could affect the individual's decision to rely on the AI decision aid or not. In hypothesis 2a, we observed that perceived performance situational risk significantly mediated the relationship between the performance risk condition and the decision to rely on AI decision aids. This can imply that individuals experiencing higher perceived performance risk may be less willing to make the decision of relying on AI decision aids in the situation, which aligns with research suggesting that individuals reduce their reliance on technology when the risk is greater (Ezer et al., 2008; Rajaonah et al., 2008). Although only marginally significant, a similar mediating effect occurred on the relationship between the psychological risk condition and the decision to rely on AI decision aids. Solberg et al. (2022) anticipated that the perceptions of performance risk and psychological risk were two of the most important domains that could determine the decision to rely on an AI decision to carry out a decision-making task, and our findings reflect this.

Further, looking at the effect of the performance risk condition on perceived performance risk, we discovered a significant negative relationship when FDM increased. From Table 2 (and Appendix 2), we observed that respondents scoring high on FDM perceived more performance risk when presented with the manipulated performance risk scenario than respondents scoring low on FDM. Additionally, perceived performance risk decreased for respondents who were presented with the vignette scenario containing the control condition even though FDM increased (as visualized in Figure 2), which lends support to our hypothesis that individuals with a more FDM can influence the perceived risk in the situation. While only being marginally significant, these findings indicate that mindset beliefs can make performance risk factors inherent in a situation more salient, thus influencing the decision to rely on an AI decision aid to perform a decision-making task. This can indicate that an individual with FDM experiencing more perceived performance risk may choose not to rely on the AI decision aid, as the individual with fixed mindset wants to make sure they will succeed (Dweck, 2017) and choose tasks they can perform well.

Our findings suggest that an employee with high FDM will be less willing to make the decision to rely on an AI decision aid when the perceived performance risk increases, as the risk of performing poorly is higher. This is reflected in Dweck and Legget's (1998) argument of how individuals with a fixed mindset only approach situations in which they are confident their abilities can be validated.

As addressed previously, individuals with a growth mindset will positively impact individual- and organizational performance (Han & Stihea, 2020) as they tend to be more open to changes. On the other hand, individuals with a fixed mindset tend to choose work tasks they are familiar with and know they can master (Dweck & Yeager, 2019). In relation to our findings, it can be implied that employees with a FDM tend to avoid relying on AI decision aids when the perceived performance risk is high. As the technological success is rather dependent on the extent to which employees adopt the technology by accepting it and using it (Legris et al., 2003), this may impact the improvement of organizational decision-making where AI decision aid workplace technology is promoted.

7.2 Limitations and Future Research

In the following, limitations of our study and directions for future research will be discussed. First, there is a chance that social desirability bias exists among our findings, in which participants have answered questions in ways considered favorable (Adams et al., 2005). While we encouraged participants to respond as sincerely as possible in the survey, we are aware that there will always be a risk that participants may have answered to be more eager towards development of digital skills than what is actually true, i.e., they have more of a FDM than what they imply. However, some claim that social desirability is not necessarily as problematic as predicted (Ones et al., 1996).

Moreover, although we had a total of 192 respondents, we cannot exclude that there might exist a risk of a reduction in statistical power. It was expected that the overall model in hypothesis 2a was not significant because the moderation effect was only marginally significant. Yet, interesting patterns exist in the findings, and the sample size in each vignette could therefore be why these were not significant enough to be supported. Therefore, a study with a larger sample could support and enhance our findings' generalizability.

Furthermore, while hypothesis 1 was supported, only a small number of participants had experience with ERP-systems or similar, as well as experience in calculating and allocating bonuses manually. This could have jeopardized the ecological validity as the results may not reflect the real world (Bell et al., 2019). Therefore, it could be interesting for future research to examine different sectors where employees have the prerequisite knowledge and experience with AI decision aids and how their digital mindset beliefs and perception of risk could influence the decision to rely on AI decision aids. According to Solberg et al. (2022), human resources and finance sectors are industries with higher risk, thus also higher decision stakes. Conclusively, these industries could be a good place to conduct future research. Also, while we focused on perceived situational risk in this study and its relation to the decision of relying on AI decision aids, we are aware that other factors can affect this decision which could be interesting to conduct further research on. For example, the perceived trustworthiness of the trustee or the individual's propensity to trust is conceptualized in Mayer et al.'s (1995) model and contributes to explaining and influencing trust.

As mentioned previously, the external validity is often lower in vignette studies in contrast to the fact that the internal validity is often higher (Hughes & Huby, 2002; Roehling, 1999; Woehr & Lance, 1991). However, research has shown that by increasing the level of realism in the vignette experiment, the external validity can be enhanced. Based on this, we suggest for future research that the participants in the experiment are physically exposed to the situation described. This can, for example, be pictures, videos, audio, or presentations to make it even more realistic and evaluate if this can affect the results.

Lastly, according to Stuck et al. (2021), there is no standard way for assessing perceived risk in present research studies, which implies that this could be a limitation of our study. Currently, no tools exist that identify relevant risks and their significance in certain situations. Additionally, it has been pointed out that there are no validated measures of perceived risk regarding the domains used in this study. Yet, there is ongoing research in this field today that is trying to find valid scales for perceived situational risk. Therefore, it could be helpful to continue research in this area to contribute to creating a valid measure for perceived situational risk.

7.3 Practical Implications

Despite its limitations, this study brings to light noteworthy practical implications. There is an increasing trend in using AI to improve organizational decision-making tasks, and our findings can potentially provide organizations with implications for how to enhance the interrelationship between employees and AI decision aid technology.

The perception of risk is of great importance to understanding individuals' behavior toward working with AI, and organizational members can benefit from understanding this. Research suggests that the perceived risk is dependent on the situation (e.g., Solberg et al., 2022; Stuck et al., 2021). Thus, different domains of perceived risk can be more relevant than others in specific industries or sectors. However, as we discovered in this study, perceived performance situational risk impacted the decision to rely on AI decision aids in relation to the workplace. Leaders in organizations can therefore benefit from understanding how to reduce the perception of performance risk in situations when working with AI decision aids. For example, the leaders within the organizations could emphasize that the outcome of relying on the technology should not affect the leader’s perceived performance of the employee.

Furthermore, our findings suggest that digital mindset beliefs impact the perceived risk inherent in the situation, thus it can affect their decision to rely on AI. Therefore, it would be helpful for organizational leaders to be aware that employees possess different mindsets and consider this when working with AI decision aid tools. Leaders within these organizations can be mindful in terms of FDM thinking by giving these employees extra attention when bringing in new AI tools. As individuals with a fixed mindset are more prone to turn down help because they fear they can be perceived as incompetent by others (Dweck & Yeager, 2019), leaders could be mindful of this when implementing and using AI tools. For example, they can organize training sessions for all employees regardless of their digital mindset beliefs. Those with a more FDM can perceive themselves as just as competent as the others as they go through the same training. This may also further help reduce FDM among employees in an organizational setting.

Moreover, it has been stressed that individuals rarely hold only one mindset but can be more fixed-oriented in one situation and more growth-oriented in another (Dweck, 2015), thus, the perception of risk in the situation, therefore, depends on the mindset. As our findings suggest that digital mindset can influence the perception of performance risk in a given situation, it could be beneficial for leaders in organizations to be aware of this. Furthermore, understanding how employees can perceive risk in different situations based on their mindsets can further improve how leaders approach the employees when introducing AI decision aid tools and tasks. Therefore, leaders can benefit from not generalizing the employees for having a FDM or GDM in every work-related situation, as this is not necessarily always the case.

8.0 Conclusion

In summary, this study sought to examine how domains of perceived situational risk could influence the decision of relying on AI decision aids and how an individual's digital mindset beliefs could make the risk factors inherent in the situation more salient. Specifically, the study revealed that there was a negative relationship between perceived performance-, social-, and psychological situational risk, and the decision to rely on an AI decision aid. This implies that an individual's perceived situational risk influences the decision to rely.

Moreover, although only marginally supported, the study identified that an individual's digital mindset could impact the perception of risk factors inherent in a situation, thus it can influence the decision to rely on an AI decision aid. Overall, our results highlight the importance of trust in AI decision aid technology and digital mindset as concepts for future exploration, as it can be fundamental for establishing the role of AI technology in organizations moving forward. In conclusion, we hope our findings in this study can provide insight for future research and guide employees working with AI decision aids in organizational settings.

9.0 References

Adams, S. A., Matthews, C. E., Ebbeling, C. B., Moore, C. G., Cunningham, J. E., Fulton, J., & Hebert, J. R. (2005). The effect of social desirability and social approval on self-reports of physical activity. *American journal of epidemiology, 161*(4), 389-398.

Aguinis, H., & Bradley, K. J. (2014). Best Practice Recommendations for Designing and Implementing Experimental Vignette Methodology Studies. *Organizational Research Methods, 17*(4), 351–371. https://doi.org/10.1177/1094428114547952.

Argyris, C. (1975). Dangers in applying results from experimental social psychology. *American Psychologist, 30*, 469-485.

Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 6*, 128-138.

Banerjee, A., Chitnis, U., Jadhav, S., Bhawalkar, J., & Chaudhury, S. (2009). Hypothesis testing, type I and type II errors. *Industrial psychiatry journal, 18*(2), 127.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173.

Bell, E., Bryman, A. & Harley, B. (2019). *Business research methods* (Fifth edition). Oxford University Press.

Cavanaugh, G. F., & Fritzsche, D. J. (1985). Using vignettes in business ethics research. In L. E. Preston (Ed.) *Research in corporate social performance and policy* (pp. 279-293, Vol. 7). London: Jai Press.

Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of applied psychology, 92*(4), 909.

De Jong, B. A., Dirks, K. T., & Gillespie, N. (2016). Trust and team performance: A meta-analysis of main effects, moderators, and covariates. *Journal of applied psychology, 101*(8), 1134.

Dweck, C. (1986). Motivational Processes Affecting Learning. *American Psychologist, 41*(10), 1040-1048.

Dweck, C. (2015). Carol Dweck revisits the growth mindset. *Education Week*, 35(5), 20-24.

Dweck, C. (2017). *Mindset: Changing the way you think to fulfil your potential*. Hachette UK.

Dweck, C. S. (2006). *Mindset: The new psychology of success* (1st ed). New York: Random House.

Dweck, C. S., Chiu, C.-y., & Hong, Y.-y. (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological inquiry, 6*(4), 267-285.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review,* 95, 256 –273 https://doi.org/10.1037/0033-295X.95.2.256.

Dweck, C.S. & Yeager, D. S. (2019). Mindsets: A View From Two Eras. *Perspectives on Psychological Science, 14*(3), 481–496. https://doi.org/10.1177/1745691618804166.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Eirug, A. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 101994.*

Ezer, N., Fisk, A. D., & Rogers, W. A. (2008). Age-related differ- ences in reliance behavior attributable to costs within a human- decision aid system. *Human Factors*, *50*, 853–863.

Fox-Glassman, K. T., & Weber, E. U. (2016). What makes risk acceptable? Revisiting the 1978 psychological dimensions of perceptions of technological risks. *Journal of Mathematical Psychology, 75*, 157–169. https://doi.org/10.1016/j.jmp.2016.05.003.

French, B., Duenser, A., & Heathcote, A. (2018). Trust in Automation. A Literature Review.

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *The Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057.

Groom, V., & Nass, C. (2007). Can robots be teammates? Benchmarks in human-robot teams. *Interaction Studies*, 8, 483-500.

Han S. J. , & Stieha, V. (2020). Growth Mindset for Human Resource Development: A Scoping Review of the Literature with Recommended Interventions. *Human Resource Development Review, 19*(3), 309–331. https://doi.org/10.1177/1534484320939739.

Hancock, P. A., Billings, D. R., Schaefer, K. E, Chen, J. Y. C, De Visser, E. J, & Parasuraman, R. (2011). A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction. *Human Factors, 53*(5), 517–527. https://doi.org/10.1177/0018720811417254.

Hayes, A. (2022). *The PROCESS macro for SPSS, SAS, and R*. https://www.processmacro.org/index.html.

Heslin, P. A., Vandewalle, D., & Latham, G. P. (2006). Keen to help? Managers' implicit person theories and their subsequent employee coaching. *Personnel Psychology, 59*, 871-902.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: integrating empirical evidence on factors that influence trust. *Human Factors, 57*, 407-434.

Hox, J. J., Kreft, I. G., & Hermkens, P. L. (1991). The analysis of factorial surveys. *Sociological Methods & Research, 19*, 493-510.

Hughes, R., & Huby, M. (2002). The application of vignettes in social and nursing research. *Journal of Advanced Nursing, 37*, 382-386.

Jacoby, J., and Kaplan, L. (1972). The components of perceived risk. In M. Venkatesan (Ed.), *Proceedings, 3rd Annual Conference* (pp. 382-393). Chicago: Association for Consumer Research.

Kane, G. C., Palmer, D., Nguyen Phillips, A., Kiron, D., & Buckley, N. (2017). Achieving Digital Maturity. *MIT Sloan Management Review, 59*(1).

Koller, M. 1988. Risk as a determinant of trust. *Basic and Applied Social Psychology 9*(4), 265–276.

Kray, L. J., & Haselhuhn, M. P. (2007). Implicit negotiation beliefs and performance: Experimental and longitudinal evidence. *Journal of Personality and Social Psychology*, 93, 49 – 64. https://doi.org/10.1037/0022- 3514.93.1.49.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & management, 40*(3), 191-204.

Levy, S. R. Stroessner, S. J., & Dweck, C. S. (1998). Stereotype Formation and Endorsement. *Journal of Personality and Social Psychology*, 74(6), 1421–1436. https://doi.org/10.1037/0022-3514.74.6.1421.

Lipman, V. (2017). Practical Tips To Help Companies Develop A Digital Mindset. *Forbes*. https://www.forbes.com/sites/victorlipman/2017/07/19/practical-tips-to-help-companies-develop-a-digital-mindset/#67931e947fe5.

Mayer, R. C., & Davis, J. H. (1999). The effect of the performance appraisal system on trust for management: A field quasi-experiment. *Journal of Applied Psychology, 84*(1), 123–136. https://doi.org/10.1037/0021-9010.84.1.123.

Mayer, R., Davis, J., & Schoorman, F. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review, 20*(3), 709-734. https://doi.org/10.2307/258792.

McCarthy, J. (2007). What is artificial intelligence? Stanford, CA: Stanford University. http://www-formal.stanford.edu/jmc/whatisai.pdf.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making. *California Management Review, 61*(4), 84–109. https://doi.org/10.1177/0008125619862256.

Ones, D. S., Viswesvaran, C., & Reiss, A. D. (1996). Role of social desirability in personality testing for personnel selection: The red herring. *Journal of applied psychology, 81*(6), 660.

Park, E., Jenkins, Q., & Jiang, X. (2008). Measuring trust of human operators in new generation rescue robots. In *Proceedings of the JFPS International Symposium on Fluid power* (Vol. 2008, No. 7-2, pp. 489-492). The Japan Fluid Power System Society.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods, 40*(3), 879-891.

Rajaonah, B., Tricot, N., Anceaux, F., & Millot, P. (2008). The role of intervening variables in driver–ACC cooperation. *International Journal of Human-Computer Studies*, *66*, 185–197.

Roehling, M. V. (1999). Weight-based discrimination in employment: *Psychological and legal aspects.Personnel Psychology, 52*, 969-1016.

Roselius, T. (1971). Consumer rankings of risk reduction methods. *Journal of Marketing, 35*, 56-61.

Scandura, T. A., & Williams, E. A. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management Journal, 43*, 1248-1264.

Schaefer, K. E., Chen, J. Y. C, Szalma, J. L., & Hancock, P. A. (2016). A Meta Analysis of Factors Influencing the Development of Trust in Automation. *Human Factors, 58*(3), 377–400. https://doi.org/10.1177/0018720816634228.

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257.

Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journals of Business Research, 123,* 588-603. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.09.068.

Solberg, E., Kaarstad, M., Eitrheim, M. H. R., Bisio, R., Reegård, K., & Bloch, M. (2022). A Conceptual Model of Trust, Perceived Risk, and Reliance on AI Decision Aids. *Group & Organization Management, 47*(2), 187–222. https://doi.org/10.1177/10596011221081238.

Solberg, E., Traavik, L. E. M, & Wong, S. I. (2020). Digital Mindsets: Recognizing and Leveraging Individual Beliefs for Digital Transformation. *California Management Review, 62*(4), 105–124. https://doi.org/10.1177/0008125620931839.

Stuck, R. E., Holthausen, B. E., & Walker, B. N. (2021). Chapter 8 – The role of risk in human-robot trust. In C. Nam & J. Lyons (Ed.), *Trust in Human-Robot Interaction,* (pp. 179-194). Academic Press. https://doi.org/10.1016/B978-0-12-819472-0.00008-3.

Stuck, R. E., & Walker, B. N. (2019). Risk Perceptions of Common Technologies. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 63*(1), 1316–1320. https://doi.org/10.1177/1071181319631128.

Stuck, R. E., Tomlinson, B. J., & Walker, B. N. (2019). *The importance of incorporating risk into the study of human-automation trust* (Manuscript in Publication).

von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404–409. https://doi.org/10.5465/amd.2018.0084.

Wang, W., Qiu, L., Kim, D., & Benbasat, I. 2016. Effects of rational and social appeals of online recommendation agents on cognition- and affect-based trust. *Decision Support Systems, 86*, 48–60.

Wildavsky, A., & Dake, K. (1990). Theories of risk perception: Who fears what and why? *Daedalus, 119(4),* 41–60. https://doi.org/10.2307/20025337.

Woehr, D. J., & Lance, C. E. (1991). Paper people versus direct observation: An empirical examination of laboratory methodologies. *Journal of Organizational Behavior, 12*, 387-397.

10.0 Appendices

Appendix 1: Survey

Title of the project:
Risk and reliance on artificial intelligence

Purpose of the project:
To investigate how personal factors can influence the perceived risk of relying on artificially intelligent decision aids at work

Who is responsible?
Master students Hanna Salvesen and Helena Møller from the department of Leadership and Organizational Behavior at BI Business School under the supervision of Elizabeth Solberg.

What does participation require from you?
Participants in this study should be presently employed. The survey will take approximately 5 minutes. Your answers will be recorded electronically in the online survey platform Qualtrics. The data will be used for research purposes only.

Participation in the project is voluntary and anonymous. If you choose to participate, you can withdraw your consent at any time. No personal information will be collected that could possibly identify you. Your response is fully anonymous if you choose to participate.

Yours sincerely,
Hanna Salvesen and Helena Møller

By going forward in the survey, you confirm that you are presently employed and give your consent to participate in this study:
( ) I give my concent to participate in ENLIGSH
( ) I give my concent to participate in NORWEGIAN

Thank you for participating in our study! We will start with a few general background questions.

How old are you?
Under 20 years (1), 20-29 years (2), 30-39 years (3), 40-49 years (4), 50-59 years (5), 60-69 years (6), 70 years or older (7)

To which gender identity do you most identify?
Male (1), Female (2), Non-binary (3), Transperson (4), Intergender (5), Searching (6), Unsure (7), Do not wish to answer (8)

Are you currently working full-time or have you previously worked full-time? If so, how many years?
Less than a year (1), Between 1 and 2 years (2), Between 2 and 5 years (3), Between 5 and 10 years (4), More than 10 years (5), Not applicable – I have never worked full-time (6)

The following questions concern your beliefs about your technological abilities and skills. Please indicate to what extent you agree with each statement. There are no right or wrong answers. Just answer as sincerely as you can.

You have a certain amount of technological ability, and you cannot really do much to change it
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

Your technological ability is something about you that you cannot change very much
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

You can always substantially improve your technological skills through effort
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

You can learn new technological skills, but you cannot really change your basic technological ability

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

The following questions concern your preferences for demonstrating and developing competence. There are no right or wrong answers. Just answer as sincerely as you can.

Please indicate to what extent you agree with each statement below:

I am willing to select a challenging work assignment that I can learn a lot from

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I often look for opportunities at work to develop new knowledge and skills

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I enjoy challenging and difficult tasks at work where I'll learn new skills

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

For me, development of my work ability is important enough to take risks

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

Please indicate to what extent you agree with each statement below:

I am concerned about showing that I can perform better than my coworkers

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I try to figure out what it takes to prove my ability to others at work

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I enjoy it when others at work are aware of how well I am doing
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I prefer to work on projects where I can prove my ability to others
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

Please indicate to what extent you agree with each statement below:

I would avoid taking on a new task at work if there was a chance I would appear rather incompetent to others
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

Avoiding looking incompetent at work is more important to me than learning a new skill
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I am concerned about taking on work tasks that could reveal that I had low ability
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

I prefer to avoid situations at work where I might perform poorly
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

Vignette

In this last part of the survey, you will be presented with a short scenario describing a situation where you need to make a decision. Please read the scenario carefully before answering the questions that follow. There are no right or wrong answers. Just answer as sincerely as you can.

Control

You work at a large company. In your role, you have the responsibility to calculate annual monetary bonuses for employees. Your company has a module for its Enterprise Resource Planning (ERP) system that can calculate annual bonuses automatically, but the system is not mandatory to use (so you can still do it manually, as you always have before). The ERP module is said to be very reliable and can calculate bonuses more quickly than when it is done manually, which could free you up to do other work.

Annual bonus calculations are due next month.

Please indicate how strongly you agree with the statement below:
In this situation, I would choose to calculate and allocate bonuses using the automated ERP system module
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

To what extent do you experience some risk in relying on the automated ERP system module in this situation?
To a very small extent (1), To a small extent (2), To neither a small or large extent (3), To a large extent (4), To a very large extent (5)

Please indicate what type of risk you associate with this situation:

The risk of personal financial loss by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of failing to deliver a desired performance by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of being physically injured by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of losing your identity (i.e., the way you think of yourself) by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of looking foolish or incompetent in front of others by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of relying on the ERP-system and wasting time, convenience and effort repairing the issue if the system were to fail
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The overall risk of relying on the ERP-system, considering all sorts of factors combined
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

Are there any other types of risk you associate with this situation?

Do you have any similar work experience with calculating and allocating bonuses for employees? Select all that apply
Yes, manually (1), Yes, using ERP-system or similar (2), No (3)

Are there any additional comments you would like to make about the scenario or questions presented in this study?

Perceived Performance Risk

You work at a large company. In your role, you have the responsibility to calculate annual monetary bonuses for employees. Your company has a module for its Enterprise Resource Planning (ERP) system that can calculate annual bonuses automatically, but the system is not mandatory to use (so you can still do it manually, as you always have before). The ERP module is said to be very reliable and can calculate bonuses more quickly than when it is done manually, which could free you up to do other work.

Annual bonus calculations are due next month. You know that your boss (the director of the business unit you work for) remains skeptical about using automated systems for making decisions that have financial consequences for employees. You will have your annual review meeting with your director the week after bonuses are calculated.

Please indicate how strongly you agree with the statement below:
In this situation, I would choose to calculate and allocate bonuses using the automated ERP system module
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

To what extent do you experience some risk in relying on the automated ERP system module in this situation?
To a very small extent (1), To a small extent (2), To neither a small or large extent (3), To a large extent (4), To a very large extent (5)

Please indicate what type of risk you associate with this situation:

The risk of personal financial loss by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of failing to deliver a desired performance by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of being physically injured by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of losing your identity (i.e., the way you think of yourself) by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of looking foolish or incompetent in front of others by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of relying on the ERP-system and wasting time, convenience and effort repairing the issue if the system were to fail
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The overall risk of relying on the ERP-system, considering all sorts of factors combined
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

Are there any other types of risk you associate with this situation?

Do you have any similar work experience with calculating and allocating bonuses for employees? Select all that apply
Yes, manually (1), Yes, using ERP-system or similar (2), No (3)

Are there any additional comments you would like to make about the scenario or questions presented in this study?

Perceived Social Risk

You work at a large company. In your role, you have the responsibility to calculate annual monetary bonuses for employees. Your company has a module for its Enterprise Resource Planning (ERP) system that can calculate annual bonuses automatically, but the system is not mandatory to use (so you can still do it manually, as you always have before). The ERP module is said to be very reliable and can calculate bonuses more quickly than when it is done manually, which could free you up to do other work.

Annual bonus calculations and allocations are due from you and the other managers in your business unit next month. You know that many of the other managers remain skeptical about using automated systems for making decisions that have financial consequences for employees.

Please indicate how strongly you agree with the statement below:
In this situation, I would choose to calculate and allocate bonuses using the automated ERP system module

Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

To what extent do you experience some risk in relying on the automated ERP system module in this situation?

To a very small extent (1), To a small extent (2), To neither a small or large extent (3), To a large extent (4), To a very large extent (5)

Please indicate what type of risk you associate with this situation:

The risk of personal financial loss by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of failing to deliver a desired performance by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of being physically injured by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of losing your identity (i.e., the way you think of yourself) by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of looking foolish or incompetent in front of others by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of relying on the ERP-system and wasting time, convenience and effort repairing the issue if the system were to fail

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The overall risk of relying on the ERP-system, considering all sorts of factors combined

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

Are there any other types of risk you associate with this situation?

Do you have any similar work experience with calculating and allocating bonuses for employees? Select all that apply

Yes, manually (1), Yes, using ERP-system or similar (2), No (3)

Are there any additional comments you would like to make about the scenario or questions presented in this study?

Perceived Psychological Risk

You work at a large company. In your role, you have the responsibility to calculate annual monetary bonuses for employees. Your company has a module for its Enterprise Resource Planning (ERP) system that can calculate annual bonuses automatically, but the system is not mandatory to use (so you can still do it manually, as you always have before). The ERP module is said to be very reliable and can calculate bonuses more quickly than when it is done manually, which could free you up to do other work.

Still, you have always been acknowledged as being very competent in calculating annual monetary bonuses for employees. Annual bonus calculations are due next month.

Please indicate how strongly you agree with the statement below:
In this situation, I would choose to calculate and allocate bonuses using the automated ERP system module
Strongly disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4), Strongly agree (5)

To what extent do you experience some risk in relying on the automated ERP system module in this situation?
To a very small extent (1), To a small extent (2), To neither a small or large extent (3), To a large extent (4), To a very large extent (5)

Please indicate what type of risk you associate with this situation:

The risk of personal financial loss by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of failing to deliver a desired performance by relying on the ERP-system

Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of being physically injured by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of losing your identity (i.e., the way you think of yourself) by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of looking foolish or incompetent in front of others by relying on the ERP-system
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The risk of relying on the ERP-system and wasting time, convenience and effort repairing the issue if the system were to fail
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

The overall risk of relying on the ERP-system, considering all sorts of factors combined
Very low risk (1), Low risk (2), Moderate risk (3), High risk (4), Very high risk (5)

Are there any other types of risk you associate with this situation?

Do you have any similar work experience with calculating and allocating bonuses for employees? Select all that apply
Yes, manually (1), Yes, using ERP-system or similar (2), No (3)

Are there any additional comments you would like to make about the scenario or questions presented in this study?

Appendix 2: Conditional Effects of the Focal Predictor at Values of FDM on Perceived Performance Risk

FDM	*b*	*t*	CI 95% *Lower*	CI 95% *Upper*	*p*
1.00	-.1130	-.3389	-.7757	.5496	.7355
1.15	-.0434	-.1440	.8858	-.6417	.5550
1.30	.0263	.0971	-.5119	.5645	.9229
1.45	.0960	.3942	-.3878	.5798	.6944
1.60	.1656	.7528	-.2716	.6028	.4536
1.75	.2353	1.1653	-.1659	.6365	.2470
1.90	.3050	1.5996	-.0738	.6838	.1132
2.0453	.3724	1.9870	.0000	.7449	.0500
2.05	.3746	1.9984	.0021	.7471	.0487
2.20	.4443	2.3047	.0612	.8273	.0235
2.35	.5140	2.4959	.1048	.9231	.0144
2.50	.5836	2.5877	.1355	1.0318	.0113
2.65	.6533	2.6121	.1563	1.1502	.0106
2.80	.7229	2.5976	.1699	1.2759	.0110
2.95	.7926	2.5637	.1783	1.4069	.0120
3.10	.8623	2.5216	.1828	1.5417	.0135
3.25	.9319	2.4774	.1845	1.6794	.0151
3.40	1.0016	2.4342	.1840	1.8192	.0169
3.55	1.0713	2.3935	.1820	1.9606	.0188
3.70	1.1409	2.3558	.1786	2.1032	.0207
3.85	1.2106	2.3211	.1743	2.2469	.0226
4.00	1.2803	2.2895	.1692	2.3914	.0244

Note. N=93. b = unstandardized coefficients.