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Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy

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ABSTRACT

Drawing upon insights from the trust literature, we conducted two empirical surveys with the front-line employees of firms in Pakistan investigating the factors influencing cognitive trust in artificial intelligence (AI). Study1 consisted of 46 in-depth interviews aimed at exploring factors influencing cognitive trust. Based on the findings of Study 1, we developed a framework to enhance employees' cognitive trust in AI. We then conducted a quantitative survey (study 2) with 314 employees to validate the proposed model. The findings suggest that AI features positively influence the cognitive trust of employees, while work routine disruptions have negative impact on cognitive trust in AI. The effectiveness of data governance was also found to facilitate employees' trust in data governance and subsequently, employees' cognitive trust in AI. We contribute to the technology trust literature, especial in developing economics. We discuss the implications of our findings for both research and practice.

1. Introduction

Value creation through digital technologies relies on users' trust in those technologies (Hoff and Bashir, 2015). Consequently, if employees do not trust these technologies, organizations that are undergoing digital transformations will struggle to execute their digital strategy (Barrane et al., 2020). Digital strategy pertains to an 'organizational strategy formulated and executed by leveraging digital resources to create differential value'. Frontline employees play a detrimental role in implementing the strategy successfully as leveraging digital resources depends on their trust in emerging technologies and their ability to integrate digital resources into their work routines (Witcher & Chau, 2010). As a result, it is important for organizations to understand the factors influencing frontline employees' trust in digital technologies to execute their digital strategy effectively. In this study, we focus on the frontline employees' trust and value creation through artificial intelligence (AI) driven insights, given the critical role they play in their organizations.

Over the past few years, organizations have increasingly utilized AI to manage various tasks, and its significance is expanding in both manufacturing and service sectors (cf. McKinsey, 2022). Despite its adoption by different types of firms, many individuals lack trust in AI (Andriole, 2018). Although various studies have examined the maturity of AI, there is a need to consider human element of integrating AI by cultivating employees' trust in such technologies (Glikson & Woolley, 2020). This study responds Glikson and Woolley's (2020) call at exploring factors influencing employees' trust in value creation through AI driven insights from a human-centred approach.

AI typically defined as the ability of a machine to perform cognitive functions associated with human minds (e.g. perceiving, reasoning, learning, and problem-solving), allowing it to solve business problems (Liu et al., 2020). AI lies at the core of the fourth industrial revolution (Glikson and Woolley, 2020), often known as industry 4.0 (Shamim et al., 2016). Nevertheless, value creation through AI is a complex

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process as other tangible and intangible resources need to be integrated and utilized across organizational boundaries. According to a survey of>2500 executives and 17 leading AI experts, 40% of the organizations investing in AI are unable to report business gains from AI (Ransbotham et al., 2019), and it can even reduce the employees' job engagement (Braganza et al. 2021). This phenomenon demonstrates that despite investing in AI, many firms still struggle to effectively leverage its advantages. It highlights the importance for researchers to understand the human-technology relations and interactions from a human-based approach. Theoretical propositions made by Glikson and Woolley (2020) suggest that employees' trust in AI plays a vital role for organizations to adopt this emerging technology for value co-creation. Due to the complexity, nondeterminism of AI behaviours and its future prospect of replacing many people's work, people fear of trusting AI (McKnight et al., 2020). Empirical research indicates that perceived trust and risk influence the outcomes of adopting emerging technologies (Gu et al., 2021). The trust that users develop in AI technology is central to determine its role in organizations moving forward (Glikson and Woolley, 2020). Therefore, it is essential to investigate the factors that have the potential to enhance frontline workers' cognitive trust in AI to maximum its value.

In this context, prior organizational research has primarily considered trust to be a cognitive construct involving a rational evaluation of the trustee and situational features (Gillath et al., 2021). Trust in technology refers to people's readiness to embrace the potential risks associated with AI to achieve superior outcomes (Gillath et al. 2021). Emerging technologies offer both opportunities and risks which can differ across firms and countries adopting such technologies. While developed economies have an advantage in harnessing the emerging technologies, resource-constrained economies such as Pakistan which may face challenges due to a lack of necessary skills. In this study, we explore trust related issues specifically pertaining to AI in the context of resource-constrained economies like Pakistan.

The application of AI remains nascent in countries like Pakistan (Wahl et al., 2018), which means building trust in such technologies will require time and effort to realize the desired benefits. With the recent United Nation (UN)'s goal of reducing inequality through artificial intelligence (UN. 2017), it is important for researchers and practitioners to gain insights about how to improve workers' trust in AI in developing economies. There are two differences between developed countries and developing countries in terms of the trust and the acceptance of AI. Firstly, developing economies face institutional voids and receive scarce support from institutions to help innovations and new technologies adoption (Khan et al., 2019). Trust can be explained through institutional-based approaches that enable and encourage trust through regulative, normative, and cognitive structures (Fuglsang & Jagd, 2015). Secondly, inter-firm cooperation is also limited in developing economies (Zia et al., 2022), which could restrict organizations' abilities from enhancing their knowledge of AI through social learning, resulting in much longer to build trust in AI.

Currently, there is very limited research on the processes and mechanisms involved in building trust in AI. Thus, it is imperative to understand the organizational, personal, and technological (AI) antecedents of AI trust. This study aims to investigate the factors influencing cognitive trust in AI and AI-driven insights in a developing economy where there is a need for organizations and workers to gradually accept and adopt AI and other digital technologies to develop a sustainable economy through the value creation. Drawing on trust theories and literature, we aim to bridge this research gap.

2. Literature review

2.1. Trust-building process

Social psychology literature defines trust as the perceived credibility and benevolence of a target of trust (Kumar et al. 1995). It involves relying on trustee whom one has confidence in (Moorman, Zaltman, and Deshpandé 1992). Trust is developed through a trustor's expectations about the behaviours of trustee (Doney and Cannon, 1997). Doney and Cannon (1997) identified five distinct processes of trust development: calculative process, prediction process, capability process, intentionality process, and transference process. The calculative process involves trustor calculating the cost and reward of a target acting in an untrustworthy manner. Prediction process refers to the development of confidence that the target's behaviour can be predicted. In the capability process, the trustor accesses the trustee's capability to fulfil their commitments. The intentionality process involves evaluating targets motivation, and transference means drawing on sources from which trust is transferred to the target (Doney and Cannon, 1997). Institutional assurance and knowledge-based familiarity were added to added to Doney and Cannon (1997)'s framework by Gefen et al. (2003) and Kim (2004) and Gefen et al. (2003) respectively. Moorman et al. (1992) identified reputation of trustee, satisfaction, and experience of trustor with trustee as antecedent of trust. Ba and Pavlou (2002) also suggested that the feedback mechanism is a useful predictor of trust.

In general, trust can be 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 the other party (Mayer et al., 1995). In interpersonal relations, trust can be stimulated by rationality or emotions. When the trust is rooted in rationality, it is cognitive trust, and when it comes from emotions, then it refers to emotional trust or affective trust (Erdem & Ozen, 2003). Trust is a dynamic concept that is prone to changes based on the behaviour of trusted agents (Crisp & Jarvenpaa, 2013). Particularly cognitive trust in technology is unstable and it can change because of events such as negative news related to technology (McKnight et al., 2020), as well as security and privacy concerns (Gefen et al., 2003).

2.2. Ai-driven cognitive insights

AI, in management literature, is defined as a new generation of technologies which interact with the environment by gathering information from outside or other computer systems (Glikson & Woolley, 2020). One of the commonly used components of AI is machine learning, which is often used for activities such as prediction, pattern identification and modelling. For example, it can be applied to predict customer-buying intention; identify credit fraud; and provide an insurer with more accurate actuarial modelling (Davenport & Ronanki, 2018). It can be embedded in different applications, which makes it invisible to users without visual representation or distinguished identity such as GPS maps and search engines (Davenport and Ronanki, 2018).

People's cognitive trust in AI is subject to their perception of different AI technologies in terms of their evaluation of the outcomes associated with AI; social pressure and norms of adopting AI at workplace, and controllability of the AI. Davenport & Ronanki (2018) suggest that AI is mainly applied in three types of cognitive tasks, namely robotics & cognitive automation (e.g., transferring data from emails), cognitive insights (e.g., predicting customer preference), and cognitive engagement (e.g., chatbots). Cognitive insights can assist people in interpreting information and recognize patterns in it, including forecasting events, producing results, responding to questions, and giving instructions to other systems. AI can also evaluate its results of its actions and improve its decision systems (Ferràs-Hernández, 2018). The ability of AI to interact with the environment enables it to learn and change its behaviour following the cues in the environment (Simon and Frantz, 2003). AI usually operates in a highly complex environment, which makes it not deterministic (Danks & London, 2017). The complexity of the process of AI decision-making is usually not transparent, making it difficult for users to understand the logic behind the decisions (Glikson and Woolley, 2020). Hengstler et al. (2016)'s showed that trust is challenging to build when people lack the knowledge about technologies, particularly true in developing countries like in Pakistan where the government investment and support in such technologies is insufficient (Mangi et al. 2021). This lack of familiarity with the emerging technologies like AI could create fear, leading to low level of trust in AI and unfavourable evaluation of AI, hindering its potential usage for value-co-creation. Additionally, people may feel they are not in control of the technology due to the complexity of AI characteristics such as connectivity, cognitive ability, and imperceptibility (Canhoto & Clear, 2020). Despite of these characteristics, AI offers vital cognitive insights to organizations (cf. Davenport & Ronanki, 2018). Cognitive insight refers to the ability to evaluate thoughts and beliefs in the pursuit of thoughtful conclusions through applying external feedback from others (Van Camp et al., 2017). One common function of AI applications is cognitive insights which involves using algorithms to detect and interpret big data (Davenport & Ronanki, 2018).

2.3. Cognitive trust in artificial intelligence

Recent studies position trust, especially cognitive trust, as a strong predictor of value creation through digital technology such as AI (Hengstler et al., 2016). Cognitive trust refers to individual belief in the reliability, dependability, and competence of those whom they trust (Moorman et al., 1992). This definition extends beyond human-to-human interactions and encompasses trust in technology (Pavlou and Fygenson, 2006) including AI (Wang et al., 2016). Hoff & Bashir (2015) posit that trust entails being willing to take a meaningful risk and maintaining a positive outlook on the potential outcomes (Parasuraman & Manzey, 2010).

Cognitive trust, is essential when dealing with sophisticated technologies, especially those involving complex processes such as AI-driven cognitive insights (Glikson & Woolley, 2020). Unlike other technologies, AI technology is designed to mimic human intelligence and cognitive ability; the technology also applies complex algorithms to process large amounts of data for decision making (Glikson & Woolley, 2020). One main difference between AI technology and traditional one is that AI can interact with humans and respond to human language and behaviour (Davenport & Ronanki, 2018). In a data/AI driven organization, decision makers usually rely on AI for activities such as prediction, pattern identification and modelling (Davenport & Ronanki, 2018), which requires specialized research to develop trust in AI and understand how build trust in AI among employees. To overcome the perception of risk and uncertainty associated with emerging technologies before applying such technologies, initial trust is important for users before applying such technologies. Trust in technologies can be built by considering cognitive reputation, cost-benefit calculation, and organizational norms (Li et al., 2018). Glikson and Woolley (2020) suggested reliability, transparency, and immediacy behaviour of embedded cognitive AI as building blocks of cognitive trust in AI. Additionally, current literature acknowledges lawfulness, ethics, socio-technical robustness, privacy and governance, fairness, and accountability as enablers of trust in AI (Felzmann et al., 2019). Feedback regarding its accuracy can influence cognitive trust in embedded AI (De Visser et al., 2017). Studies have shown that people tend to trust embedded cognitive AI initially, but their trust decreases over time due to erroneous AI functions, and restoring trust takes time (McKnight et al., 2020).

The above review highlights that growing interest among scholars in cognitive trust in AI. While existing literature primarily focuses on AI features such as transparency and reliability (Felzmann et al, 2019), employee individual-level perceptions on AI have potentials to indirectly shape AI value creation (Shamim et al., 2019). However, empirical studies on this topic across different contexts are limited, particularly in developing and emerging economies characterised by weak institutional environment (Khan et al, 2019). Institutional-based approach to trust suggest that weak institutions hinder building up the sense of trust (Fuglsang and Jagd, 2015), and therefore presents a distinct context from the countries with strong institutions. Considering the complexity of building trust in AI and the scarcity of empirical studies in this area, we conducted two empirical studies, study 1 and study 2, in various firms operating in Pakistan. The following sections describe the research methods and the findings of each study.

3. Study 1: Qualitative exploration

3.1. Methodology

Data collection: Given the early inroads of emerging technologies in Pakistan, frontline employees using AI related technologies make the population of this study. The researchers conducted interviews with 46 such employees from 23 companies in the services and manufacturing sectors. These companies and participants were selected based on the expectation of information richness, and to provide us with an interesting opportunity to address the research question (Eisenhardt, 1989) The participants were from diverse sectors such as banking, insurance, consumer goods, telecommunication, and the travel industry. All the participants were front line employees having direct interaction with customers and relying on AI insights in their daily jobs. The authors contacted the senior managers and coordinators in head offices and regional offices to gain access to their employees using emerging technologies such as AI. We also used our networks to gain access to the selected firms and their employees. We started with a small number of eight initial interview contacts that fit the research criteria and invited them to participate in the study as interviewees. Subsequently, we utilized a snowball sampling technique whereby these initial participants recommended other suitable contacts who also met the research criteria. Through this method, we conducted a total of 46 interviews. For example, participants from insurance companies relying on AI-driven insights to target potential customers. Sales employees in consumer goods companies adopting AI-driven insights to plan their market visits and banking employees who use AI to evaluate customers' credit ratings and possibilities of customer default cases. All the interviewees were front line employees or front-line managers with first-hand experience of utilizing AI technologies. To ensure reliability, we recorded the interview data in a table that allowed for quickly interpretation of the results based on individual participant's records, thereby facilitating the tracking of the research progress. We validate and triangulate the information provided by our informants by archival data including customer-company chat on digital platform (without personal identifiers), meeting notes, and email exchanges (Zeng, 2022).

Prior to the interviews, interview questions were emailed to each participant, outlining the purpose and key terms of the interview. Interviews were conducted via Skype or phone calls, with the permission of the interviewees, and recorded for analysis. Anonymity of the respondents and their organizations was ensured. The interviews consisted of a set of predetermined questions, leading to sub-questions during the discussions. Seven participants were contacted for a second round of interviews to elaborate on certain topics from the first round. Out of the 46 employees interviewed, seven underwent a second interview. All interviews were conducted in Urdu, the native language of Pakistan, and later translated and transcribed into English by bilingual researchers for analysis.

Data analysis: In accordance with the principles of naturalistic inquiry (Lincoln and Guba 1985), we began analysing the data immediately after conducting the first interview. We did so by following the procedures recommended by Strauss and Corbin (1998) and utilized a replication logic in which each case was treated as its own discrete experiment (Eisenhardt and Graebner, 2007). Following this method, we analysed the data iteratively by linking them with the emerging theoretical frameworks (Strauss & Corbin, 1998). Our analysis of the interview data comprised three main steps.

Firstly, to facilitate effective expression from our informants (Suddaby, 2006), we conducted an analysis starting with a systematic breakdown of the data using an open-coding approach (Strauss and

Corbin, 1998). The transcripts were independently reviewed, and descriptive codes related to each interviewee's words were identified to document and assess the level and breadth of theme support among our informants. In cases of differing opinions, interview scripts were consulted for clarification. Similar codes were grouped into first-order categories, following the approach used by Vuori & Huy (2016), and our coding was refined through constant comparison with the conceptual framework (Fig. 1). The coding of interview transcripts continued until theoretical saturation was reached (Glaser, 2004), and a recursive process of reading the data multiple times (Lincoln and Guba, 1985) allowed for the development of an initial classification system reflecting the perspectives of our informants. Once we agreed on the initial categorizations and definitions, we proceeded to the next stage, which involved open coding by breaking the data into distinct events, acts, ideas, or incidents and assigning appropriate codes.

Secondly, after establishing the first-order categories, we proceeded to identify their relationships, developing link, and distinctions (Strauss and Corbin 1998). This comparative analysis helped us understand differences and similarities across interviews. We then made sense of the emerging practices and focussed on the areas where further analysis of the complete sample was needed (Strauss and Corbin 1998). To ensure the validity of the construct, we relied on triangulating our primary and secondary data. We continued to go back and forth between any emerging theoretical themes and the data until no new categories emerged. This iterative process allows us to sort codes into broader subgroups. Each code represented a theme, and all common frames were assigned a unique theme.

Thirdly, we identified the dimensions underlying these categories to understand how different ones fit together into a coherent picture (see Table 1). We analysed how these categories related to each other and established conceptual frameworks (Fig. 1) capturing these links.

3.2. Findings

Based on the analysis of illustrative quotes (see Table 4), we found that employee's perception on the reliability, transparency, and flexibility of AI plays deterministic roles in forming their cognitive trust in AI. The definitions of the three characteristics can be seen at Table 3 based on the existing research. Interviews also revealed that the compatibility of AI with work routines and interviewees' digital literacy could facilitate the formation of employees' trust in applying AI at workplace. Furthermore, interviews revealed an intriguing finding about the effectiveness of data governance in the organization. Although it was not our focus of the study, it turns out to be very crucial factor influencing g employees' trust in AI. Table 2 shows the frequency of factors in illustrative quotes. Based on these findings we developed a framework to enhance employees' cognitive trust in AI as shown in Fig. 1.

3.3. Perceived reliability of AI and cognitive trust in AI

The findings suggest that employees' perception of AI reliability can impact their cognitive trust in AI. Doney and Cannon (1997) trust-building framework suggests that the trustor gains confidence in predicting the trustor's behaviour through repeated and broader experience. Consistent outcomes of AI usage can contribute to building user confidence. Reliability, defined as exhibiting consistent and expected behaviour over time, plays a crucial role in establishing trustworthiness in technology (Hoff and Bashir, 2015). Respondents identified reliability as an influential factor in cognitive trust in AI. For instance, one respondent stated:

> *"I will trust more in AI-driven insights if I can see a similar pattern of AI recommendation over time. Uniformity of AI recommendation enhances my confidence and trust because it reduces uncertainty".*

Another interviewee argued that:

> *"I do not rely on AI to perform my daily routine tasks because AI requires me to change my routines frequently. I do not trust AI because it tells me to deal with a similar type of customers in a different way".*

These illustrative quotes indicate the importance of AI reliability to predict cognitive trust in AI. It shows that inconsistencies in AI-driven insights could have impact on employees' perception of AI reliability. Another illustrative example from a sales employee of the telecommunication sector is:

> *"To evaluate my performance, I tend to consider my network of relationships and strategize based on my customer interactions. While AI-driven results suggesting some potential customers, I found they also can lead to waste time if suggestions are not relevant. Hence, I prefer to work on my customer base as it gives me more confident in my approach".*

In some cases where AI-driven insights were consistent, participants

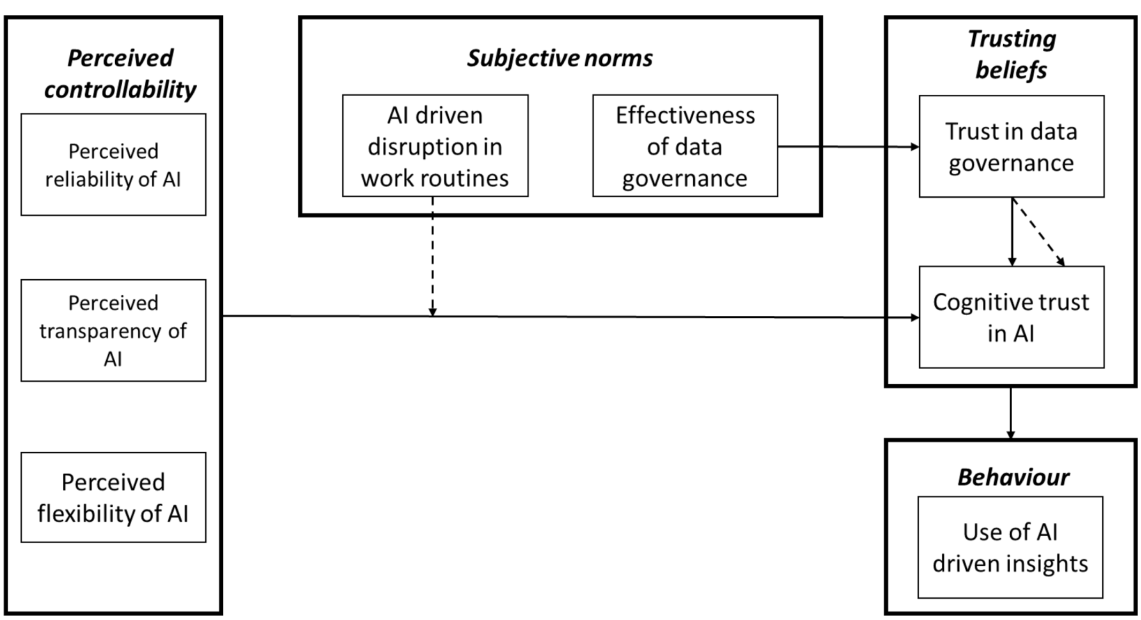

Fig. 1. Proposed framework.

Table 1
Overview of data structure.

First-order concepts	Second-order themes	aggregate themes
- The consistent pattern on AI recommendation overtime - Consistency of ways in dealing with the similar type of customers - More confidence in other ways of working such as relying on customer relationships more than value creation through AI - Positive past experience of AI-driven decisions	Perceived AI reliability	Perceived controllability
- Knowledge of AI working mechanisms - Complexity of AI system - Understanding of reasons behind AI-driven decisions - Knowing why AI recommendations conflict with own judgment - Understanding of the purpose of using AI - Knowing the logic behind AI-driven decisions.	Perceived AI transparency	
- Availability of options in a given situation - Availability of additional insights - Rigidness of AI insights - Incorporating contingencies - Compatibility with changing job properties over time	Perceived AI Flexibility	
- Authenticity of data - Check and balance on data entry procedure - Presence of fake data - Manipulation in data - Check and balance to ensure the authenticity of data - Ensuring data quality	Effectiveness of data governance	Subjective norms
- Diversion from existing key competencies - Compromising existing competitive advantage - Disruption in existing ways of doing the job - Disruption in the preferred way of working - Compatibility with work style	AI-driven Disruption in work routines	
- Perception of poor data quality - Perception of lack of good data governance - Knowledge of fake data entry - knowing that how easy or difficult it is to manipulate data in an organization	Trust in data governance	Trusting beliefs (Attitudes)
	Cognitive trust in AI → Use of AI-driven Insights	

indicated a high level of cognitive trust in AI. The participants argued that they can rely on AI-driven insights and decisions to perform their job. For example, one of the participants from a bank had the view that:

> *"AI made my job easier, I rely on AI-driven decisions to approve the credit application of clients. Most of the time these decisions are effective, and it is rare to see that an AI recommended customer is defaulting".*

These illustrative examples suggest that AI reliability is one of the building blocks of employees' cognitive trust in AI. Employees will trust more in AI-driven insights to perform their routine jobs if AI-driven outcomes are consistent and repeat the positive behaviour over time. From a broader perspective these arguments suggest that perceived AI reliability contributes towards perceived controllability, which leads to cognitive trust in AI. Controllability reflects a subjective degree of control over the performance of behaviour and not on the likelihood of producing a given outcome. It should be read as perceived control over the performance of behaviour (Ajzen, 2002). Based on these arguments we propose:

Proposition 1: *the higher the perceived reliability of AI is the more cognitive trust employees display in AI.*

3.4. AI transparency and cognitive trust in AI

The study revealed that perceived controllability of AI infrastructure is an important factor in enhancing employees' cognitive trust in AI. Specifically, AI transparency plays a significant role in this process, referring to the extent to which users can comprehend the underlying mechanisms and inner workings of the technology (e.g., AI) (Hoff & Bashir, 2015). One participant said:

"I will trust in AI if I know how it works. I cannot simply follow something when I have no idea of the processes behind it".

This illustrative quote reflects the importance of AI transparency, it indicates that if employees know how AI algorithms are set and how these algorithms recommend something related to their job, they will feel more comfortable and confident to follow AI-driven insights. Similar remarks are found in another participant:

> *"I work in sales, but my IT background enables me to understand how our system works, and how it generates recommendations for sales staff. I can understand the mechanism of AI-driven marketing analytics. We do not have many complex systems. Therefore, I can rely on AI with confidence".*

Though the main argument in the above illustrative quotes is related to IT skills and knowledge, however, it also reflects the importance of transparency i.e. knowing of back-end processes generating AI-driven insights. Other interviewees expressed similar views. For example, an employee of an insurance company mentioned:

> *"When the system suggests offering or not to offering insurance products to a client, we have to follow the recommendation. However, sometimes system recommendations are conflict with my judgment. It creates doubts in my mind because I am unable to understand the reasons for these decisions driven by AI"*

Another Illustrative example is.

> *"AI is quite new to our organization and the majority of us, including myself lack knowledge of its underlying mechanism. Our IT department never provided some training on how to use the system to perform our jobs. The training sessions offered were merely showed us how to navigate the system, without explaining what the technology is and how it operates. Even our leaders are unsure about how AI works. Once I asked one of the top managers why he thinks that following the new system of AI-driven insights can lead to better performance? He replied we do not need to understand the technology since we are not IT professionals, and we can just follow the system".*

This statement reflects transparency of AI infrastructure is one of the central factor-influencing employee's cognitive trust in AI. Technology trust literature also suggests that, without a sound understanding of the technology, it will be challenging for employees to feel they are in control of their performance by following the recommendations generated by the technologies (Ho et al., 2020). This influences employees' attitude toward the AI, which is clearly shown in one of interviewee's response:

"I feel more confident when I make decisions using my knowledge

Table 2
Frequency analysis.

Participant	AI reliability	AI transparency	AI flexibility	Digital readiness	AI compatibility with work routines	Effectiveness of data governance	Trust in data governance	Speed	Inhuman nature of AI
1	✔					✔	✔		
2		✔	✔				✔		
3	✔							✔	
4	✔	✔			✔	✔	✔		
5			✔			✔	✔		
6		✔				✔	✔		
7					✔	✔	✔		
8	✔	✔				✔	✔	✔	
9		✔	✔						✔
10	✔		✔				✔		
11	✔					✔	✔		
12		✔	✔						
13	✔					✔	✔		
14		✔			✔				
15					✔	✔	✔		
16		✔	✔						
17	✔							✔	
18		✔				✔	✔		
19	✔					✔			
20			✔		✔	✔	✔		
21	✔				✔	✔	✔		
22		✔			✔	✔	✔		
23		✔					✔		
24	✔			✔					
25			✔			✔	✔		
26	✔						✔		
27					✔	✔			
28	✔	✔				✔	✔		
29			✔		✔	✔	✔		
30	✔	✔							
32				✔		✔	✔		
33	✔	✔							
35						✔	✔		
36		✔			✔				
37		✔	✔			✔	✔		
38	✔						✔		
40	✔		✔				✔		
41						✔	✔		
42	✔	✔	✔			✔	✔		
43	✔								✔
44						✔	✔		
45							✔		
46	✔	✔				✔	✔		
Total	20	19	12	2	10	25	30	3	2

Table 3

Key terms	Description	Source
AI reliability	Reliability refers to exhibiting the same and expected behaviour over time, and it is crucial for technology trustworthiness	(Hoff & Bashir, 2015)
AI transparency	It reflects the level to which the underlying mechanisms and inner logics of technology (e.g. AI) are apparent to users	(Hoff and Bashir, 2015)
AI flexibility	We define AI flexibility as the elasticity of AI and its ability to consider changing situations.	Authors
Work routines	Work routines refer to temporal structures that are often used as a way of accomplishing organizational work; these are repeated patterns of consistent behaviour, bound by customs and organizational rules	(Feldman, 2000)
Data governance	Data governance refers to the exercise of authority and control over the management of data and defining how those data assets may be used	(Abraham et al., 2019)
Cognitive trust	Cognitive trust refers to individual beliefs about the reliability, dependability, and competence of the trustee.	(Moorman et al., 1992)

and expertise because I know the logic and reasons behind my decision.”.

Cognitive trust is based on knowledge which is accumulated from observing trustee’s actions (Johnson and Grayson, 2005). This observation requires openness and transparency of trustee and clear communication mechanism (Norman et al., 2010). Lack of AI transparency can lower the cognitive trust, potentially leading to AI abuse by users. For example, a study on Uber drivers revealed that the absence of AI transparency caused them to resist and abuse the system (Lee et al, 2015). Similarly, Möhlmann and Zalmanson (2017) reported that Uber drivers do not trust AI-driven managerial decisions due to a low level of transparency, leading to resistance. Gilikson and Woolley (2020) argue that transparency increases cognitive trust by reducing the fear of possible technology errors. Providing a rationale for a potential mistake made by AI can positively influence cognitive trust (Dzindolet et al, 2003). These findings and scholarly arguments in existing literature suggest the following proposition:

Proposition 2: the higher the AI transparency is the more cognitive trust employees display in AI.

AI flexibility and cognitive trust in AI.

Table 4
Illustrative quotes.

Second order themes	Illustrative quotes
Reliability	*"I will trust more in AI-driven insights if I can see a similar pattern of AI recommendation over time. Uniformity of AI recommendation enhances my confidence and trust because it reduces uncertainty"* *"I do not rely on AI to perform my daily routine tasks because AI requires me to change my routines frequently. I do not trust AI because it tells me to deal with a similar type of customers in a different way* *"To evaluate my performance, I tend to consider my network of relationships and strategize based on my customer interactions. While AI-driven results suggesting some potential customers, I found they also can lead to waste time if suggestions are not relevant. Hence, I prefer to work on my customer base as it gives me more confident in my approach".* *"AI made my job easier, I rely on AI-driven decisions to approve the credit application of clients. Most of the time these decisions are effective, and it is rare to see that an AI recommended customer is defaulting"*
Transparency	*"I will trust in AI if I know how it works, how I can simply follow something when I have no idea of the processes behind it"* *"I work in sales, but my IT background enables me to understand how our system works, and how it generates recommendations for sales staff. I can understand the mechanism of AI-driven marketing analytics. We do not have many complex systems. Therefore, I can rely on AI with confidence"* *"When the system suggests offering or not to offering insurance products to a client, we have to follow the recommendation. However, sometimes system recommendations are conflict with my judgment. It creates doubts in my mind because I am unable to understand the reasons for these decisions driven by AI"* *"AI is quite new to our organization and the majority of us, including myself lack knowledge of its underlying mechanism. Our IT department never provided some training on how to use the system to perform our jobs. The training sessions offered were merely showed us how to navigate the system, without explaining what the technology is and how it operates. Even our leaders are unsure about how AI works. Once I asked one of the top managers why he thinks that following the new system of AI-driven insights can lead to better performance? He replied we do not need to understand the technology since we are not IT professionals, and we can just follow the system".* *"I feel more confident when I make decisions using my knowledge and expertise because I know the logic and reasons behind my decision"*
Flexibility	*"When I perform my job based on my knowledge and experience, I have many more options to select a most feasible solution in the given situation, However, AI does not provide this flexibility"* *"When I discuss a deal with a potential client, sometimes I get additional insights from the detailed discussion which is not incorporated in AI system. As a result, my personal view contradicts AI-driven insights. It is mainly because AI is unable to consider the new information that I gain from my latest conversation with my client. This creates a certain level of rigidity, which limits value creation through AI"* *"AI does not know what I need in the given time, being a sales employee, my work and performance requirements are very dynamic. Sometimes I need to show greater compliance with SOPs, sometimes I need to generate more sales, sometimes I need to focus on increasing the availability of our product across retailers in my territory, and sometimes especially at the end of the month I am worried about my monthly sales target. I think AI is not flexible enough to help me with changing priorities over time to meet the dynamic nature of my job"*
Effectiveness of data governance	*" I know how data is inputted into our information system and as the data is not authentic, I do not see the point of depending on AI. "* *"There lacks proper monitor of how data is entered into our systems, which creates opportunity for individuals to manipulate data to create positive performance image. Unfortunately, this infrastructure is built on artificial data created by some employees who are confident that they won't get caught due to the lack of effective data checks. In essence, there is no way to verify the authenticity of the data entered our system".* *"For example, if someone achieves monthly target one week before the end of the month, he/she will not enter all the sales into the system that are generated in the last week. They will save it to include it in their next month sales, just because they do not need it this month for their target achievement. This is happening across the country in thousands of our distribution setups. Therefore, if management wants to plan something following AI-driven insights, which are based on such data entered by people across the country, they will not gain an accurate picture because of the manipulation in data entry. I believe that management is aware of the malpractice, and they do not rely on AI-driven insights".* *"Our organization is adopting AI but doing little to ensure quality and authenticity of data. This is a major reason why I do not rely on AI "*
Disruption in work routines	*"Although I acknowledge the benefits of AI for my colleagues, it depends on our main strength that we use to achieve our objectives. My main strength is the customer relationships I have built over several years to achieve my sales and marketing objectives. If I need a high volume of sales at a given time, I will call the customer (Anonymous1) and customer (Anonymous2) who are always willing to help me out. This is my main strength, which makes me competitive, and this is how I am doing my job. AI does not align with my preferred approach to work. Even my company asks me to use AI, I only use AI-driven insight for compliance purposes but does not consider it valuable. I view it as a disruption to my work and believe that relying on AI could potentially harm my competitiveness".* *"I follow system generated leads (AI-driven) to plan my day because It simplifies job. For example, I receive a list of potential new customers, which I focus on, and it has been successful for me. I no longer have to spend time in finding and tracing customers myself. As a result, I think I am performing well compared against my annual objectives. Therefore, AI is working well for me"* *"Despite my comprehension of how AI operates and the reliability and usefulness of its recommendations, I still do not believe it is suitable for me. I feel it is not compatible with my work style and I strongly feel that I can perform better without it"*

The interview data revealed that the level of perceived flexibility of AI may impact employees' cognitive trust in AI-driven insights. Several participants mentioned flexibility or rigidity of AI when discussing their cognitive trust in AI. Those perceive AI-driven insights are agile and responsive to changes expressed higher levels of cognitive trust in AI. Conversely, those perceived AI-driven insights are rigid tended to express lower levels of trust in AI-driven insights. For example, one of the participants stated that:

"When I perform my job based on my knowledge and experience, I have many more options to select a most feasible solution in the given situation, However, AI does not provide this flexibility."

One bank employee argued that:

"When I discuss a deal with a potential client, sometimes I get additional insights from the detailed discussion which is not incorporated in AI system. As a result, my personal view contradicts AI-driven insights. It is mainly because AI is unable to consider the new information that I gain from my latest conversation with my client. This creates a certain level of rigidity, which limits value creation through AI".

Another illustrative example from a sales employee in a consumer goods firm is:

"AI does not know what I need in the given time, being a sales employee, my work and performance requirements are very dynamic. Sometimes I need to show greater compliance with SOPs, sometimes I need to generate more sales, sometimes I need to focus on increasing the availability of our product across retailers in my territory, and sometimes especially at the end of the month I am worried about my monthly sales target. I think AI is not flexible enough to help me with changing priorities over time to meet the dynamic nature of my job".

These illustrative quotes indicate that employees value flexibility in AI, and their perception of AI rigidity hinders their cognitive trust in AI-driven insights. Additionally, AI flexibility contributes to employees' sense of control over the technology and their ability to use it effectively. The finding indicates that AI could not provide personalized data-driven insight to meet individual employees' specific need in given context. As a result, employees may feel less in control of the technology, leading to decreased trust in AI.

Doney and Cannon (1997) framework suggested that a trustor assesses the target's ability to serve their purpose. It is rational to argue that personalization and individual relevance can enhance the perception of capability to fulfil the purpose, leading to increased cognitive trust. In the context of AI, personalization and flexibility are viewed as indicators of of intelligence which enhance cognitive trust (Glikson and Woolley, 2020). The flexible and prosocial behaviour exhibited by AI can be perceived as an agent's personality influencing the perception of a high level of agreeableness that positively influences cognitive trust in the agent (Andrews, 2012). For example, level of personalisation provided by different AI-based recommendations agents can have positive effect on cognitive trust of users (Komiak and Benbasat, 2006). Thus, we propose:

Proposition 3: *the high AI flexibility is the more cognitive trust employees have in AI.*

Effectiveness of data governance, trust in data governance and cognitive trust in AI.

This study's findings indicate that employees' lack of trust in data governance is the primary factor that affects their cognitive trust in AI. This can be attributed to the inadequate data governance practices prevalent within their organizations, which allows individuals to manipulate data to their advantage. Consequently, employees have little faith in data governance, leading to low trust in AI. Data governance involves the exercise of authority and control over data management, defining how data assets may be used (Abraham et al, 2019). From the quotes provided, we argue that the effectiveness of data governance influences cognitive trust in AI through the mediating role of employees' trust in data governance. In additional, several respondents indicated their concern over the effectiveness of data governance in the organization when asked about their cognitive trust in AI. Some of the illustrative examples are given below.

One of the sales employees in a consumer goods firm said:

"I know how data is inputted into our information system and as the data is not authentic, I do not see the point of depending on AI. "

The above statement reflects the importance of data governance in building trust and it is also consistent with Fuglsang et al.'s (2015) argument that institutional weaknesses can impede trust sense-making in the given context. Another participant argued that.

"There lacks proper monitor of how data is entered into our systems, which creates opportunity for individuals to manipulate data to create positive performance image. Unfortunately, this infrastructure is built on artificial data created by some employees who are confident that they won't get caught due to the lack of effective data checks. In essence, there is no way to verify the authenticity of the data entered our system".

The same respondent added that:

"For example, if someone achieves monthly target one week before the end of the month, he/she will not enter all the sales into the system that are generated in the last week. They will save it to include it in their next month sales, just because they do not need it this month for their target achievement. This is happening across the country in thousands of our distribution setups. Therefore, if management wants to plan something following AI-driven insights, which are based on such data entered by people across the country, they will not gain an accurate picture because of the manipulation in data entry. I believe that management is aware of the malpractice, and they do not rely on AI-driven insights"

The issue of data governance and lack of trust in it is particularly common among sales employees in the consumer goods sector. However, employees in other sectors also indicated the similar data governance issues. For example, one of the employees in the telecommunication sector said that:

"Our organization is adopting AI but doing little to ensure quality and authenticity of data. This is a major reason why I do not rely on AI".

These arguments and illustrative examples lead us to propose that effectiveness of data governance is an important influencer of employees' cognitive trust in AI, and employees' trust in data governance mediates this relationship. This argument is consistent with institutional-based approach to trust which suggest that institutional strength/weakness in terms of regulative, normative, or cognitive structure influence the trust. The effectiveness of data governance reflects subjective norms, and employee trust in data governance reflects attitude i.e. trusting beliefs. Attitude refers to an individual's favourable or unfavourable evaluation of performing a particular behaviour and subjective norms capture a person's perception of important elements of specific situation. Attitudes come from underlying attitudinal beliefs and subjective norms depends on normative belief. Attitudinal beliefs refer to the expected behavioural outcome (Pavlou & Fygenson, 2006).

Strong regulative, normative, and cognitive structures can enable and inspire trust-relations among people at the interpersonal and inter-organizational level (Fuglsand and Jagd, 2015). Such regulative processes also enhance sense making among employees which improves trust (Weber and Glynn, 2006; Fuglsand and Jagd, 2015). These findings lead to the following proposition:

Proposition 4: *Effectiveness of data governance stimulates trust in data governance which leads to cognitive trust in AI.*

AI-driven disruption in work routines.

Our findings indicate that if AI is disrupting the existing work routines, employees will be unlikely to adopt AI in their work. Furthermore, AI compatibility with work routines influences the relationship of AI infrastructure features (i.e., reliability, transparency, and flexibility) with cognitive trust in AI. Work routines refer to temporal structures that are often used to accomplish organisational work; these are repeated patterns of consistent behaviour, bound by customs and organisational rules (Feldman, 2000). If AI does not align with employees' work routines, its reliability, transparency, and flexibility become irrelevant as employees perceive it as a disruption. Work routines, which involve repeated and consistent patterns of behaviour guided customs and organizational rules are considered an efficient way to accomplish organizational work (Feldman, 2000). Several employees emphasized that AI disruption in work routines or compatibility of AI with work routines plays a crucial role in determining their trust in AI. For instance, a participant from a consumer goods company stated that:

"Although I acknowledge the benefits of AI for my colleagues, it depends on our main strength that we use to achieve our objectives. My main strength is the customer relationships I have built over several years to achieve my sales and marketing objectives. If I need a high volume of sales at a given time, I will call the customer (Anonymous1) and customer (Anonymous2) who are always willing to help me out. This is my main strength, which makes me competitive, and this is how I am doing my job. AI does not align with my preferred approach to work. Even my company asks me to use AI; I only use AI-driven insight for compliance purposes but does not consider it valuable. I view it as a disruption to my work and believe that relying on AI could potentially harm my competitiveness".

A contrasting illustrative quote from an employee of an insurance company is:

"I follow system generated leads (AI-driven) to plan my day because It simplifies job. For example, I receive a list of potential new customers, which I focus on, and it has been successful for me. I no longer must spend time in finding and tracing customers myself. As a result, I think I am performing well compared against my annual objectives. Therefore, AI is working well for me".

Another illustrative example reflecting the role of AI-driven disruption in work routine is:

"Despite my comprehension of how AI operates and the reliability and usefulness of its recommendations, I still do not believe it is suitable for me. I feel it is not compatible with my work style and I strongly feel that I can perform better without it".

These examples illustrate the significance of AI's compatibility with employee work routines in establishing employee cognitive trust in AI. When AI-driven disrupts work routines, employees perceive that relying on AI can negatively affect performance. Consequently, it impedes employees from building cognitive trust in AI, regardless of the reliable, transparent, and flexible of AI infrastructure. From the broader perspective, AI-driven disruptions represent new subjective norms that can influence perceived controllability and trusting beliefs.

The work system theory suggests that employees should follow certain work routines within a given work system (Alter, 2013). The assumption is that work routines should be aligned with users, technology, information, and other resources being utilized (Laumer et al, 2016). Misalignment between technology and work routines can result in disruption, leading to technology failure (Wei et al, 2005) and incompatible business standards (Davenport, 1998), conflicting cultures (Wagner and Newell, 2004), conflicting values (Allen, 2005), power struggle (Scott and Wagner, 2003) and clashes between institutional logics (Sia and Soh, 2007). We suggest that AI-driven disruption in work routines might affect the trust related outcomes of AI reliability, transparency, and flexibility. Therefore, we suggest that:

Proposition 5: *AI-driven disruption in work routines lowers the effect of AI reliability, transparency, and flexibility on cognitive trust in AI.*

Based on these findings we propose the following framework. Furthermore, a few participants talked about digital literacy, the speed of AI, and the inhuman nature of AI that could influence their cognitive trust in adopting emerging technologies. However, due to very low frequency, we did not include these factors in our analysis. The proposed framework is shown in Fig. 1 and Table 3 explains the key terms.

4. Discussion of results

Our qualitative explorations show that employees' cognitive trust in accepting AI at workplace may be influenced by their perceptions of AI characteristics such as reliability, and transparency. These finding is consistent with the theoretical suggestion made by Glikson and Wolley (2020). Additional to Glikson and Wooley (2020)'s findings, our research suggest that flexibility as an additional factor contributing to the cognitive trust in AI. Our findings indicate that AI-driven disruption in work routines negatively influence the trust related outcomes of AI transparency, reliability, and flexibility. It highlights that the importance of aligning AI with work routines, which is in line with strategic management literature's recommendation that resources should be aligned with individual's work in the organization to fully leverage their potential (Witcher & Chau, 2010). Technology management literature also posits that technological infrastructure should be aligned and compatible with individuals and organizational systems to gain benefits from technology adoption (Laumer et al., 2016).

Furthermore, we draw attention to a significant issue, especially in a developing economy, which is the lack of effective data governance as a foundational obstacle to creating value through AI and nurturing employees' trust in such technologies. Ineffective data governance mechanisms lead to a lack of trust among employees, which consequently hinders their trust in AI-driven insights. Based on our findings, we contend that trust in technology-related governance mechanisms related to technology is a prerequisite to building cognitive trust in emerging technologies. These findings are particularly noteworthy in the context low-tech developing economies. However, the situation may differ in in high-tech developed economies, warranting a comparative analysis on this topic for future research.

Study 2: Quantitative validation.

4.1. Methodology

Sample and data collection. The population of this study comprises employees in Pakistani firms who have implemented AI in their business operations. We used the same initial sample of study 1 for conducting qualitative interviews and subsequently expanded our sample size with the help of study 1 participants to conduct a wider quantitative survey to confirm the findings of study1. Snowball sampling was initially employed to distribute structured questionnaires to employees within the same companies as in study 1. Subsequently, the survey was expanded to other firms by reaching out to HR and senior managers in accessible regional offices/branches. The survey was limited to Pakistani employees working in multinational firms in Pakistan and Pakistani joint-stock companies with foreign participation. A list of these companies is available at the official website of the State Bank of Pakistan i.e. https://www.sbp.org.pk/publications/iipp/2008/AppendicesCompList.pdf. According to the State Bank of Pakistan, 81 foreign firms in Pakistan and 698 Pakistani joint-stock companies have foreign participation. Contact details were taken from the website of each company. We contacted more than 400 firms, out of which 112 firms responded positively to our request to participate in our survey. All these firms were large scale enterprises with over 200 employees. We requested these firms to provide us with the contact details of relevant people in their organization who could distribute the questionnaire link to other employees. We created an online link using google forms for this purpose. As a result, we received 314 usable responses, all from front-line employees or front-line managers.

Common method bias. To mitigate the effect of common method bias, we took several steps. For example, we ensured the anonymity of respondents and randomized the items in the questionnaire. The statistical check was also satisfactory, i.e., Harman single factor test suggests that a single factor explains only 48.49% of the variance, which is not significant to contaminate the results. This approach is consistent with existing literature (Yang, Secchi & Homberg, 2018).

Measures. The questionnaire consisted of a combination of adapted and self-developed items. AI transparency was measure by adapting four items from Vaccaro and Echeverri, (2010). Cognitive trust in AI was measured by adapting five items from Johnson and Grayson, (2005). Four self-developed items following the insights from Glikson and Woolley (2020) were used to measure AI reliability. AI-driven disruption in work routines was measure through four self-developed items.

The effectiveness of data governance was measure by four items from Nisar el al. (2020). Trust in data governance was measure by four items drawn from Abraham, Schneider and Vom Brocke (2019). All the items are measured using a seven-point Likert scale ranging from strongly disagree to strongly agree.

5. Results

Reliability and validity. Construct reliability was assessed using Cronbach's alpha, with all constructs showing values higher than 0.7, indicating good reliability (George, 2011). Convergent validity was assessed based on construct factor loadings (>0.65), average variance extracted (AVE) and composite reliability (CR) (>0.5), and AVE being less than CR for each construct. To establish discriminant validity, Fornell and Larcker's (1981) approach was followed. the AVE of each construct should be more than the squared correlation among constructs (Fornell & Larcker, 1981). Results in Table 6 show that the AVE of each construct is higher than its squared correlation with all other constructs, which indicates discriminant validity. The chi-square of the model is 4007.27 and the R-square of the dependent variable is 0.75. Mean and standard deviations are also shown in Table 6. The findings in Table 5 and Table 6 support strong convergent and discriminant validity of the constructs.

Path analysis. Structural equation modelling is employed to validate the proposed framework in study1. Firstly, we tested the direct relationship between cognitive trust in AI and AI transparency, reliability, flexibility, and AI-driven disruption into work routines. Results indicate that cognitive trust in AI is positively related to AI transparency (β = 0.24, $p < 0.001$), AI reliability (β = 0.19, $p < 0.001$) and AI flexibility (β = 0.09, $p < 0.05$). These findings confirm the propositions drawn in study 1 and support that the AI-driven disruptions in work routine is negatively related to cognitive trust in AI (β = -0.11, $p < 0.001$) Table 7.

We then examined the mediation effect of trust in data governance on the relationship between the effectiveness of data governance and cognitive trust in AI. Our results support the hypothesis that trust in data governance mediate the relationship completely, as the direct effect of effectiveness of data governance is insignificant (β = *0.06*, $p > 0.05$) in the absence of trust in data governance. These findings align with the qualitative analysis conducted in study 1.

Table 5
Convergent validity.

Variable	Items	Factor loadings	AVE	CR	Cronbach's alpha
AI transparency	T1	0.79	0.73	0.91	0.88
	T2	0.89			
	T3	0.89			
	T4	0.83			
AI reliability	R1	0.84	0.75	0.92	0.89
	R2	0.86			
	R3	0.88			
	R4	0.88			
AI flexibility	F1	0.84	0.77	0.93	0.90
	F2	0.89			
	F3	0.88			
	F4	0.88			
Cognitive trust in AI	CT1	0.79	0.71	0.92	0.89
	CT2	0.90			
	CT3	0.90			
	CT4	0.86			
	CT5	0.74			
AI-driven disruption in work routines	DWR1	0.87	0.76	0.92	0.89
	DWR2	0.87			
	DWR3	0.89			
	DWR4	0.86			
Effectiveness of data governance	EDG1	0.88	0.80	0.94	0.91
	EDG2	0.88			
	EDG3	0.91			
	EDG4	0.90			
Trust in data governance	TDG1	0.86	0.81	0.94	0.92
	TDG2	0.92			
	TDG3	0.93			
	TDG4	0.87			

Furthermore, results support the negative moderation of AI-driven disruption in work routines in the relationship between AI flexibility and cognitive trust in AI (β = -0.08, $p < 0.05$). However, the moderating effect of AI-driven disruption in work routine in the relationship of cognitive trust in AI with AI transparency (β = 0.05, $p > 0.05$) and AI reliability (β = -0.04, $p > 0.05$) was no found to be significant. Overall, the quantitative analysis validates the model proposed in study 1, except for the moderating role of AI-driven disruption in work routines in the relationship of cognitive trust in AI with AI transparency and AI reliability.

5.1. Discussion of results

The results of Study 2 validate the framework proposed in study1 and are consistent with existing literature. Quantitative analysis of data validates that cognitive trust in AI is positively related to AI transparency, reliability, and flexibility, as suggested by Glikson, and Woolley (2020) and found in study 1. This indicates that employees are more likely to trust AI-driven insights when they understand how AI works, experience consistent outcomes and perceive a certain level of flexibility in AI.

Study 2 confirms the argument proposed in study 1 that AI-driven disruption in work routines has a negative influence on employee cognitive trust in AI. If AI requires employees to change their work routines, they are less likely to rely on AI, especially if they think that they can perform better using existing methods. The quantitative investigation also confirms that trust in data governance mediates the relationship between the effectiveness of data governance and cognitive trust in AI. In fact, trust in data governance shows the strongest relationship with cognitive trust in AI, which is consistent with the highest frequency of trust in data governance found in study1.

Furthermore, descriptive statistics reveal that majority of employees in developing economies such as Pakistan do not trust AI, feel that AI disrupts their work routines, and consider data governance mechanisms ineffective, and do not trust data governance. These findings align with study 1 and suggest that trust in technology governance is a prerequisite for gaining cognitive trust in technology, as also emphasized in study 2. Therefore, the quantitative analysis of data collected through a wider empirical survey validates the proposed model in study1.

5.2. Theoretical contributions (Study 1 and study 2)

Our study makes several contributes to existing literature. Firstly, we expand the research on trust building process by highlighting controllability and relatability, along with subjective norms as important factors in trust building process (cf. Benbya, Pachidi, & Jarvenpaa, 2021; Glikson & Woolley, 2020). Specifically, we integrated such processes within the context of AI trust and its antecedents, as perceived by frontline employees in a developing economy where emerging technologies are posing the risks and opportunities for firms. This is an underexplored area, and our study sheds light on the factors that can influence trust in AI-driven insights. We proposed and tested a framework that examines the interconnection between controllability, subjective norms, attitudes towards AI characteristics, employee individual factors, and organizational factors to establish trust in AI driven insights. We argue that controllability factors influence attitudes and beliefs related to trust in AI, while subjective norms affect trust outcomes regarding AI characteristics. Our research shows that subjective norms can disrupt work routine and influences controllability factors and trusting beliefs. This framework enhances the current limited understanding of trust-building mechanism in AI adoption.

Secondly, this study makes a significant contribution to the trust literature by providing important insights into the factors that influence

Table 6
Discriminant validity.

Factors	Mean	SD	1	2	3	4	5	6	7
AI-driven disruption in work routines	4.48	1.90	***0.76***						
AI flexibility	3.21	1.73	−0.39	***0.77***					
AI reliability	3.24	1.76	−0.29	0.65	***0.75***				
AI transparency	3.45	1.78	−0.28	0.64	0.80	***0.73***			
Cognitive trust in AI	3.14	1.76	−0.48	0.73	0.72	0.70	***0.71***		
Effectiveness of data governance	3.18	1.86	−0.33	0.62	0.45	0.38	0.67	***0.80***	
Trust in data governance	3.13	1.92	−0.42	0.64	0.50	0.44	0.77	0.79	***0.81***

Note: AVE is given at diagonal in bold.

Table 7
Path analysis.

Path	Direct effects β/t-value	indirect effects β/t-value	Total effects β/t-value	Moderating effect β/t-value	Results
AI transparency → Cognitive trust in AI	0.24***/6.10				Supported
AI reliability → Cognitive trust in AI	0.19***/4.65				Supported
AI flexibility → Cognitive trust in AI	0.09*/2.53				Supported
Effectiveness of data governance → Trust in data governance	0.79***/				Supported
Trust in data governance → Cognitive trust in AI	33.06				Supported
Effectiveness of data governance → Trust in data goernance → Cognitive trust in AI	0.40***/8.04			0.05/1.46	
AI-driven disruption in work routines → Cognitive trust in AI(AI-driven disruption in		0.32***/7.71	0.38***/		Supported
work routines)	0.06/1.69		10.08	−0.004/0.10	Supported
(AI transparency) → Cognitive trust in AI(AI-driven disruption in work routines)	−0.11***/				
(AI reliability) → Cognitive trust in AI(AI-driven disruption in work routines)	4.91			−0.08*/2.28	Not supported
(AI flexibility) → Cognitive trust in AI					
					Not supported
					Supported

Note: *** $P < 0.001$; ** $P < 01$; * $P < 0.05$.

cognitive trust in AI in a developing economy with weak institutional environment. In the context of technology trust, we argue that, in addition to trust in the technology itself, it is also essential to develop user trust in the governance and management of technologies. It adds to institutional-based approach to trust and builds on the general findings of Fuglsand and Jagd (2015), which suggest that the strength and weakness of institutions in terms of regulative, normative, and cognitive structure influence trust in technology. The study establishes that the perceived effectiveness of technology governance plays a vital role in shaping users' cognitive trust in AI-driven insights. To the best of our knowledge, this is one of the initial studies to explore and examine the effectiveness of data governance as a predictor of cognitive trust in AI and to examine trust in data governance as a mediator in this relationship (Benbya et al., 2021) given that trust and control issues are becoming important in the adoption of AI.

Furthermore, this study empirically examined Glikson and Wolley (2020) theoretical views on the influence of trust on acceptance of AI. The findings of this work support Glikson and Wolley's argument that the AI characteristics such as transparency, reliability and flexibility play a crucial role in forming employees' trust in AI adoption at workplace. Particularly in the context of AI, the study addresses the important question that why some organizations failed to create value from AI, even after making significant investments in AI. The study argues that this failure is due to a lack of trust in AI-driven insights among employees, which can be attributed to the absence of AI transparency, reliability, flexibility and most importantly, ineffective data governance systems within the organization. Finally, the study also emphasizes the important role of AI compatibility with employee work routines, which is a significant contribution to information management literature. Furthermore, we explored and empirically validated these interactions initially through qualitative enquiry, then through a wider empirical survey for quantitative analysis. While existing literature suggests these factors are critical influencers of cognitive trust, this study fills a gap in the literature by empirically testing these relationships.

This study makes an empirical and contextual contribution by focusing on a low-tech developing economy to draw attention to the barriers to technology (AI) and the trust-related issues that exist there. It is important to address the challenges related to technology acceptance and value creation in the context of developing economies because the approach developing economies take to technology and the way they drive value from it is different from those of developed economy (Shamim, Zeng, Khan & Zia, 2020).

5.3. Managerial implications

This study offers rich implications for organizational managers who are looking to implement AI in their organizations or struggling to create value from their existing AI infrastructure. To foster the development of cognitive trust and value creation through technology, managers should not restrict their focus to AI infrastructure, but also consider organizational and individual employee factors. if there is a lack of cognitive trust in AI among employees, investments in AI infrastructure are less likely to produce the intended outcomes.

Developing cognitive trust is a complex undertaking. Managers must ensure that AI infrastructure is transparent, reliable, and flexible. When implementing AI in organizations, managers should ensure that users have adequate knowledge of how AI operates and its underlying mechanisms. This can be achieved through various training and orientation sessions. Adopting and implementing AI is not solely about procuring the best technology and infrastructure. It should be a gradual and well-planned process to avoid creating a perception of disruption in employees 'work routines.

Managers, especially in developing economies, need to enhance their data governance mechanisms to foster employees' trust in data governance, which is a prerequisite of cognitive trust in AI. To enhance the effectiveness of data governance, managers should define employees' roles and responsibilities clearly, develop a data business strategy, policies, standards, and procedures and establish clear metrics for performance measurement. Compliance monitoring is also very important to enhance data governance. Furthermore, providing relevant training to employees can help to enhance data governance (Abraham et al, 2019). Following these mechanisms, managers can enhance the effectiveness of data governance in their organizations, which develops employees' trust in data governance and lead to superior cognitive trust in AI-driven insights.

6. Limitations and future research

This study has some limitations and future research suggestions. The context of this study is limited to developing economies, which can be different to those of developed and emerging economies. Future research should investigate these issues in the context of developed and emerging economy contexts to increase the generalizability of the findings and to provide comparative analysis. Future research should also further explore the factors enhancing the effectiveness of data governance leading to superior cognitive trust.

CRediT authorship contribution statement

Saqib Shamim: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Methodology, Formal analysis. **Yumei Yang:** Conceptualization, Writing – original draft, Writing – review & editing, Project administration. **Najam Ul Zia:** Conceptualization, Data curation, Writing – review & editing. Zaheer Khan: Conceptualization, Writing – review & editing, Supervision, Project administration. **Syed Muhammad Shariq:** Conceptualization, Funding acquisition, Review, Resources.

Declaration of Competing Interest

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Appendix A

We modified the base questions according to the respondent's job. We started with 8 main questions which then lead to several sub questions which were different in each interview.

We tried to make questions more relevant to front line employees by connecting it with their daily job. For example.

To employee of insurance companies…

Suppose if AI automatically analyse available information/data and suggest you not to offer insurance policy a potential customer or give you a lead to contact a potential customer to mature a sale:

To bank employees…

Suppose if AI automatically analyse available information/data and suggest you not to open account/or issue a credit card or personal loan to a potential customer:

To sales employees of consumer goods…

Suppose if computer/information system automatically analyse available information/data and suggest you a market visit plan then:

1- Why you will or will not AI generated suggestion?
2- If you follow computer-generated suggestion, then how will it influence your work?
3- What makes you uncomfortable to follow this kind of computer/information system driven leads?
4- How do these AI generated leads influence your performance?
5- What you like about involvement of AI driven suggestions in your work?
6- What you dislike about technology driven leads or suggestions to do your tasks?
7- Please share example of when AI generated leads positively or negatively influenced your performance.
8- What should be done to improve your trust in AI driven insights?

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