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ADAPTING THE 3S-MODEL FOR INVESTIGATING TRUST IN ARC SOLUTIONS IN THE DANISH CONSTRUCTION INDUSTRY

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SUMMARY: Automated solutions to building compliance checking has been slow in its implementation in the Danish construction industry. *Mainly* socio-technical *barriers,* such as trust in automation *challenge the spread of technological advances from research and development*. This paper studies the *trust* relationship *of* Architectural, Engineering, and Construction (AEC) professionals *towards* Automated Rule Checking (ARC) systems in Denmark. *The 3S-model from the field of cognitive psychology was employed to help understanding the varying ways people assess information credibility. Three hypotheses were tested through experimentation to investigate the significance of different information features, and pertaining user characteristics on human-automation trust behaviors in the domain of ARC. Although the highly specified research area targeted a relatively small demographic within the Danish construction industry, the findings present an interesting new perspective on the common characteristics and trust behaviors of the end user. With the refinement of the framework's application, the 3S-model can elucidate the many factors that are believed to influence technology acceptance within the industry. This research aims to contribute to the development of ARC solutions with a front-end viewpoint on trustworthiness.*

KEYWORDS: *BIM; ARC; BMC; Automated Rule Checking; Automation; Automated Design/Decision Aids; Trust; Socio-Technical*

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1. INTRODUCTION

Numerous studies concluded positive impacts of implementing Automated Rule Checking (ARC) from project cost reduction (Beach et al., 2015, Eastman et al., 2009, Greenwood et al., 2010), design productivity (Hjelseth, 2009, Dimyadi and Amor, 2013), to communication between Architectural, Engineering and Construction (AEC) experts (Sobhkhiz et al., 2021). ARC in this domain refers to checking the compliance of Building Information Modeling (BIM) models to a set of predefined, computer-based rules; it is typically applied in regulation compliance checking (El-Diraby, 2019). Hjelseth (2015) similarly defined BIM-based Model Checking (BMC) solutions and regarded them as "one of the best ways to illustrate the power of relevant information in BIM-files". Despite the benefits, it is reported that ARC falls short of commercial use in relation to the maturity of the technology in the research area (Revfik et al., 2014, Amor and Dimyadi, 2021). The findings of several experts in this field suggest that socio-technical challenges are the main barriers to implementation (Gade and Svidt, 2021, Lucas and Vijayarao, 2019, Sobhkhiz et al., 2021), that are present both on legislative, organizational, and individual levels. Gade and Svidt (2021) further argues that research around BMC faces a dearth of social science perspectives, and that understanding human behavior would shed light to the depths of these already identified issues. One such perspective within the individual-level is the trust relationship between human and computer.

When interacting with technology, people utilize such cooperative behavioral patterns that are associated with interpersonal relationships (Nass, Moon, Carney, 1999). Hence, trust formation towards a computer works similarly as towards another human, especially in a complex problem-solving situation (Lewandowsky, Mundy, Tan, 2000). The role of trust in human-automation interaction is well researched among fields involving elevated levels of risk, where trust is critical for task completion. Hoff and Bashir (2015) collected empirical evidence influencing trust from 127 studies, among which the most common types of automation were decision selection aids, such as combat identification-, fault management-, and risk detection aids. French et al. (2018) compiled research around trust in automation in a comprehensive literature review, which indicated growing popularity in the studies of semi-autonomous cars, decision aids, unmanned autonomous vehicles, and robotics.

Similar research in the AEC domain is relatively scarce. So far, Gade and Svidt (2021) shed light on some socio-technical challenges (i.e., transparency and flexibility) regarding the design and practical use of BMC systems. Furthermore, Gade et al. (2021) discussed the role of trust in the adoption of BIM systems, where factors influencing the trustworthiness of BIM technologies were identified through qualitative interviews. In order to enhance the use of BIM functionalities and further its development, they addressed the necessity of designing more trustable systems, which can be attained through understanding the trust relationship between the user and the system. It follows that, the importance of trust is expected to grow in the AEC Industry in accordance with the spread of autonomous technologies in architecture studios and construction sites.

Motivated by the above, this paper aims to examine trust between AEC professionals and BIM-based automated technologies by integrating a model from the field of information technology, namely the 3S-model established by Lucassen and Schraagen (2011). They proposed a framework for trust in information, where relationships are drawn between individual differences and information features that people choose to base their judgment on when evaluating information. According to the study, certain individual characteristics, namely domain expertise, information skills and source experience enable the user to notice and interpret semantic, surface or source features of the information, respectively. Hence, the framework (3S-model) categorizes information aspects as either semantic, surface or source features. These features are regarded as strategies one may choose to judge the credibility of an information (i.e., assess the trustworthiness of the information).

To better understand trust behaviors in the AEC domain, as well as to contribute to design considerations aiming for broader technology acceptance, we aim to investigate the following research question: *What is the significance of different information features, and pertaining user characteristics on human-automation trust behaviors in the domain of Automatic Rule Checking?*

This paper examines the theories of trust formation in human-computer relationships, then, through experimentation, hypotheses are tested to assess the significance of information characteristics that are displayed within an ARC user interface. The limitations are discussed following the results. This paper concludes with a discussion of the research experiment, limitations and recommendations for further research, as well as a summary and acknowledgements.

2. THEORY

2.1 Definition of trust

The matter of trust is a widely used research topic across multiple fields of studies, such as in economics (Glaeser et al., 2000), psychology (Evans and Krueger, 2009), and information technology (Mcknight et al., 2011). Many different approaches were taken to examine trust, which has left the field lacking a generally recognized definition. Trust is most commonly defined as a specific “psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another” (Rousseau et al. 1998), while Evans and Krueger (2009), describe trust as a “mental construct for social functioning and economic behavior”, making it clear that the definition of trust depends on the context in which it is used. Lee and See (2004) defined trust in the context of human-automation relationships, by considering the role of trust in mediating the interaction. They adapted the Theory of Reasoned Action (Fishbein and Ajzen, 1975) which distinguishes between belief, attitude, intention, and behavior.

Belief formation includes information about an object of belief, the perceiver’s attributes, and his or her experience. The relation of these three components forms a subjective probability judgement, which is automatically evaluated to acquire an attitude towards the object. Attitude can be described as “a person’s general feeling of favorableness or unfavorableness toward some stimulus object” (Fishbein and Ajzen, 1975). Attitude and intention are related to each other; however, intention examines the probability of an action rather than an object, which then determines the behavioral action.

Lee and See (2004) proposed that trust is most suitable as an attitude that oscillates between information processing and utilization. Information is processed concurrently with information assimilation, which leads to belief formation. Once a belief is formed, ‘Trust evolution’ occurs, where an attitude is formed upon the established beliefs. Thereafter, the processed information is taken into utility during ´Intention formation´, when the trustor evaluates the probability of taking an action. Between ‘Trust Evolution’ and ‘Intention Formation’ lies the trustor`s attitude, a general demeanor *to* the trustee which prognoses the intention *with* the trustee. When new information is provided, the process begins anew. Accordingly, for the scope of the study trust is defined as “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability.” (Lee and See, 2004 p.54).

Human-automation trust is a one-directional relationship, where trust is the trustor’s (human) attitude towards the trustee (computer). In the remainder of the paper, *user* refers to the trustor (who gives trust), and *system* refers to the trustee (subject of trust). The medium of transmission between the two members is a display, where information mediates the relationship.

2.2 Factors influencing trust

Hoff and Bashir (2015) integrated empirical evidence from human-automation trust relationship studies into a three-layer trust model that organizes existing literature. The analysis resulted in three levels of variability of trust in automation: dispositional-, situational-, and learned trust. Factors that stem from an individual`s enduring attitude towards automated systems are dispositional, thus independent from context or a specific system. These long-term tendencies can both arise from biological and environmental influences (e.g., personality traits, gender, cultural identity). Situational trust can be described as such internal and external variables that depend on the context of interaction with an automated system. This includes the user`s short-term characteristics (e.g., self-confidence, mood, subject matter expertise), and environmental conditions of current interaction (e.g., task difficulty, workload, perceived risks/benefits). Learned trust variables concern the user`s past experiences with automated systems and the automated system`s running performance. It can be divided into initial and dynamic learned trust, where initial learned trust measures trust based upon pre-existing knowledge relative to the system, whereas dynamic learned trust represents trust during interaction.

According to Lee and See (2004), trust is based on two critical elements: the focus of trust, and the information supporting trust. On one side, focus of trust is a user characteristic that defines what exactly is to be trusted, which can be considered along various levels of detail. For example, trust can be focused either on the overall system, a function within the system, or on a specific mode within the function. The ability to differentiate between the distinct levels of detail, thus being able to reflect trust accordingly, is defined as functional specificity. However, the degree of functional specificity depends on the availability of information across all levels of detail. Therefore, trust is also based upon the information shared via the entity to be trusted. Information can support trust by means of demonstrating the system's abilities, generally about its performance, process, and purpose (Mayer et al., 1995). Performance describes the system's ability to perform tasks, process explains the underlying mechanisms of the system, while purpose conveys the designer's intent for the system. Explaining these aspects on different levels of detail may enable users to calibrate their trust to better match the system`s capabilities, i.e., setting their trust to be more appropriate.

2.3 The framework for investigating trust

In Lucassen and Schraagen`s (2011) 3S-model, information is described along the dimension of three types of features: semantic, surface, and source. The study identified different methods one may take to evaluate the credibility of information, specifically, the aspects of information one utilizes when forming a credibility judgment. Similarly to Fishbein and Ajzen (1975), who established that belief is influenced by the availability of information and the user's experience, the 3S-model also conceptualizes that trust depends on information features and user characteristics. Based on the prominence-interpretation theory (Fogg, 2003), certain personal characteristics enable the user to notice, and give value or meaning to distinct aspects of information. Therefore, contrasting types of information only become prominent if the user has relevant knowledge to interpret them.

Semantic features represent the information´s meaning-holding components, those that are associated with the content of an information (e.g., accuracy, completeness, scope, neutrality). Evaluating semantic content requires familiarity in the subject matter, otherwise the user cannot assess the correctness of the information. Those without sufficient expertise in the subject area can bring to bear their information skills to utilize surface features, those aspects that relate to the presentation of the content (e.g., length, references, pictures, writing style). Information skills are generic abilities referring to effectively recognizing, processing, and using the information that is needed, and when it is needed (American Library Association Presidential Committee on Information Literacy, 1989). Education level is proved to be a good indicator of one's skillfulness in analyzing information (Lucassen et al., 2013). They furthermore found that the degree of this ability is proportionate to the extent to which users utilize surface features. Source features contain elements that are interpreted with past experience with the source. This strategy is a passive evaluation based on dispositional beliefs, rather than actively processing the information at hand.

To summarize, trust in automation is formed similarly to interpersonal trust, where the user develops an attitude towards the system based on information, which the system provides through a display (Lee and See, 2004). Variances between users, their environment, and the context of interaction (Hoff and Bashir, 2015) explain that people differ in what information they find the most prominent for interpretation (Fogg, 2003). Lucassen and Schraagen (2011) proposed three categories of information features (surface, semantic, source), as three main focuses of trust. The choice between these categories depends on the user`s characteristics and the availability of information. The next section will present how the information features of the 3S-model are hypothesized to be identifiers of trust-formation behaviors.

2.4 Hypotheses

This section summarizes the existing literature that gives way to establishing the hypotheses of the experiment. The hypotheses are aimed to investigate into the research question posed in the introduction.

Domain expertise, which enables the qualitative processing of semantic features, has its own specific evaluation behavior with regard to one's expert area. In the context of regulatory compliance assessment with BMC, one side of expertise is hypothesized to be based upon building regulation codes specific to one's discipline, in addition to competency in using BIM. According to Lucassen and Schraagen (2011), semantic content can be utilized by those only who have at least some domain expertise in the topic at hand, thus the 3S-model can be used to predict the knowledgeability of users by investigating the information features they pick during a subjective credibility evaluation. As such, by examining those who derive their judgment from semantic features, the 3S-model can be used to assess main user characteristics that define domain expertise:

H1: Domain expertise can be identified by investigating the competencies of those who base their trust judgment on semantic features.

In their literature review, Hoff and Bashir (2015) collected several studies revolving around the influence of past knowledge and experience on the trust formation process towards automation. They categorized this variability as initial learned trust, which refers to evaluations made of a system prior to the current interaction. This can either be drawn from an external source (e.g., reputation, gossip, video) or built on personal experience. Initial learned trust can mostly enhance the user's understanding of the system's purpose and process; therefore, performance can alter trust significantly during the current interaction. In regards with the 3S-model, source features are passively interpreted through the user`s source experience, and the degree of its influence depends on the strength of one's pre-existing attitude towards the source (Hilligoss and Rieh, 2008). Hence, this hypothesis aims to investigate any bias caused by an initial opinion about the source in the context of ARC, as well as to further examine its strength in the trust formation process through source familiarity.

H2: Positive or negative source experience prior to interaction influences the development of trust positively or negatively respectively.

Lee and See (2004) claimed that the availability of information is a key design consideration, as substantiating system functions from several aspects provides more detailed information which the user can utilize during a trust judgment. Enhancing the information supporting trust through attributional abstraction envelopes the three general bases of trust (performance, process, purpose) in human-machine systems, as identified by Lee and Moray (1992). Although, the mere availability of information cannot influence the way users choose to evaluate the system.

According to the prominence-interpretation theory (Fogg, 2003), users are attracted to such information that they find valuable for their own judgments. Furthermore, following Metzger`s (2007) framework, the type of evaluation regarding trust is mainly dependent on the user's motivation and ability. By combining these two predictions, the 3S-model conceptualizes that the influence of information cues is mediated by specific user characteristics (Lucassen and Schraagen, 2011). Empirical data from Gade and Svidt's study (2021) also shows that some users are interested in learning the system`s logic in detail, while others only seek validation to its correctness. Therefore, this paper hypothesizes that users' preferred trust strategy won`t be influenced by the number of cues in either of the information feature categories:

H3: Adding to the displayed information along the dimension of attributional abstraction will not expand the range of users in either of the trust strategies.

3. METHOD

This section describes the experimental design in detail. The participants selection pool, the data collection methods are explained, and the variables (both independent and dependent) are shown to clarify how the experiment can answer the earlier stated hypotheses.

3.1 Experimental Design

The experiment was designed to repeat the experiment made by Lucassen and Schraagen in 2011, where the 3S-model was initially applied. The original experiment was conducted as an online survey where participants answered a few questions about themselves, studied a screenshot of one of several Wikipedia articles, and answered two questions; one explicitly asked participants if they trusted the information, and an optional second one to reason their answer. This study repeats much of this process, but Wikipedia was replaced by a Danish-developed plug-in part of project BART: Building's Automatic Rule Checker (Byggeriets Automatiske Regel Tjek), tailored to scrutinize BIM-models for compliance against the Danish Building Regulations (BR18). The plug-in operates in Solibri Model Checker (SMC), which is a software program designed for quality assurance and control of digital building projects with functions which can perform collision control, BIM validation, and compliance checking via rules that can be customized to fit the user's needs. Partaking in the experiment was limited to construction professionals working in Denmark. Danish fluency was an expectation since the experiment was conducted in Danish. The survey was distributed online via subject relevant networks, as well as in-person at a national conference.

In the beginning, participants received an introduction to the experiment and were informed of the length of the questionnaire *("about five minutes")*. First, six questions were asked about participants' general expertise in the industry: highest education level, profession, expert area, years of work experience, and the usual project types and sizes they work with. Then, their confidence levels were assessed on a 5-point Likert scale in two sets of skills, specifically those related to ARC, and secondly to the Danish Building Regulations 2018 (BR18). BR18 regulation chapters were chosen based on the currently available chapters in the BART plug-in: *access conditions, sewage,* *fire safety*, *layout*, *moisture and wet rooms*, *energy consumption*, and *ventilation*. The final two items of the questionnaire assessed familiarity with SMC, and experience with the software (in terms of contentment).

Participants then continued to the next section of the experiment, where they were given a brief introduction to SMC and told that after viewing an image of an example rule check, two questions would follow regarding their opinion of what they have seen. They were encouraged to examine the image thoroughly as they will not be able to return after clicking forward. Thereafter, participants were presented with one randomly assigned screenshot from SMC. All screenshots presented a sample model which was checked against a BR18 code concerning the width of hallways (the model violated the minimum requirement of 1.3 meters) as is shown in Fig. 1. The screenshots were manipulated along the dimension of attributional abstraction, by information cues on the user interface (rule description, function description, model requirements, parameters), as seen on Table 1. The final questions after scrutinizing the screenshot were a closed question about their trust *("Do you trust the information presented to you in the picture on the previous page?")*, and an open-ended question asking for a rationale to their answer.

Table 1. Description of Conditions

Condition 1	*BR18 rule extract (purpose)*
Condition 2	*BR18 rule extract (purpose) + description of function (process) + model requirements (performance) + parameters (process and performance)*
Condition 3	*Parameters (process and performance)*

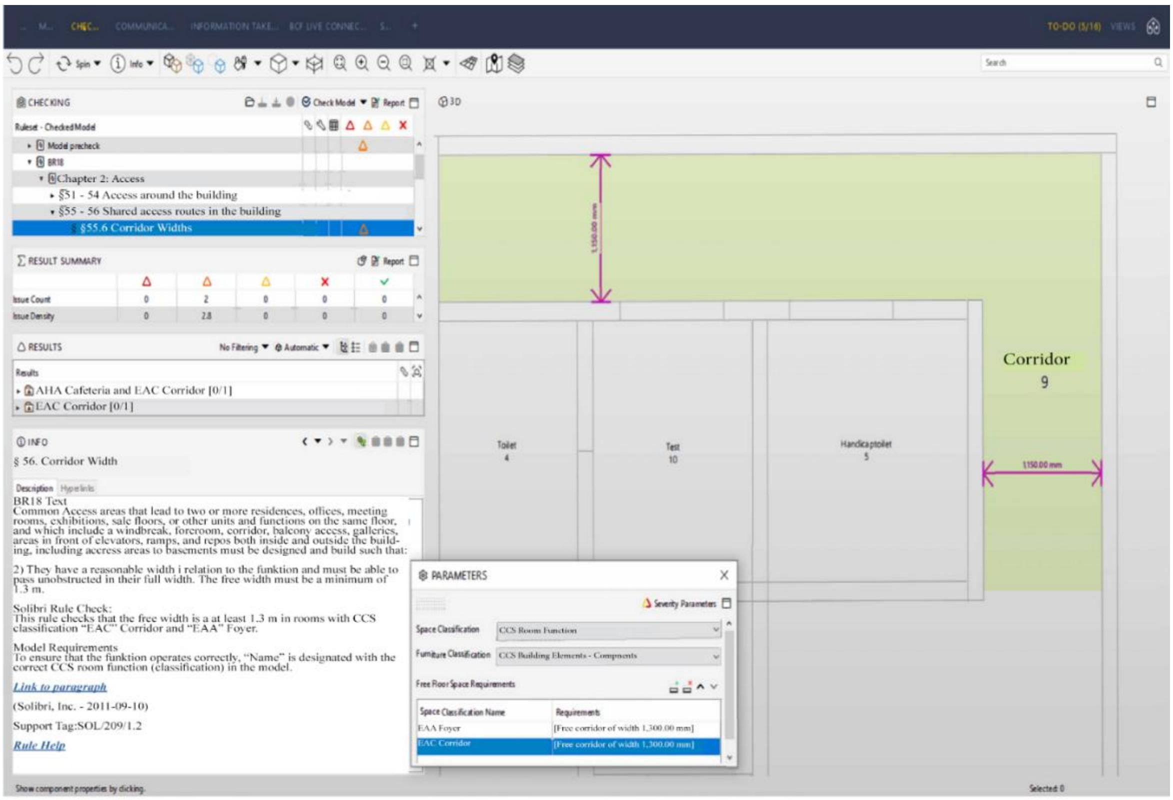

Fig. 1: Condition 2 as seen by participants during the experiment.

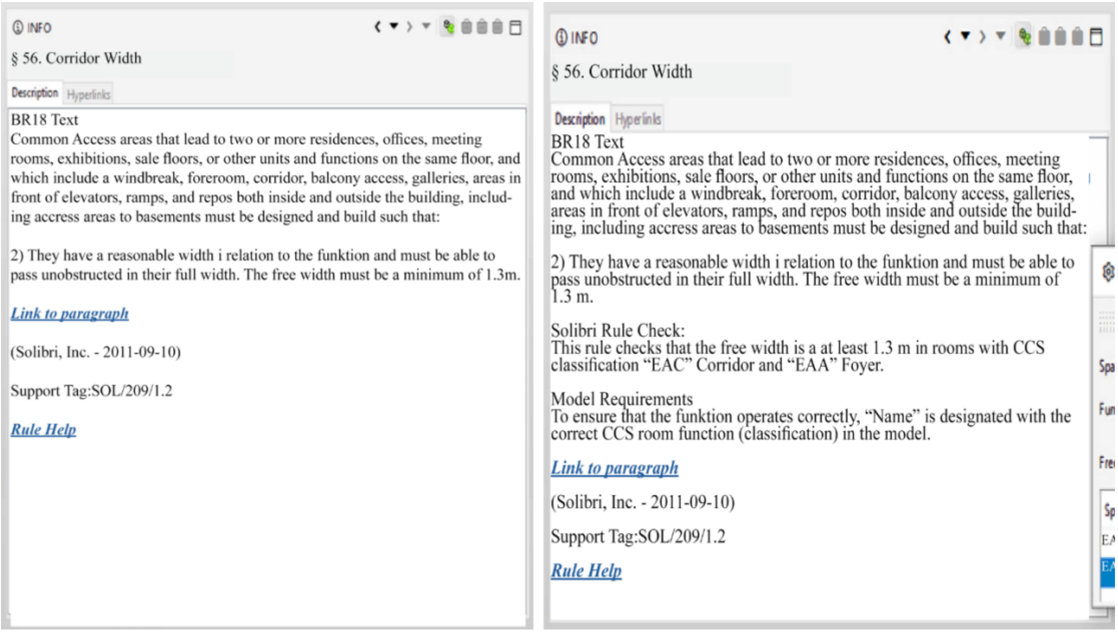

Fig. 2: Variations in text (left: Condition 1; right: Condition 2). Condition 3 only shows Parameter window without the rule description seen above.

3.2 Independent Variables

The following sections outline the dependent and independent variables within the experiment.

Expertise: This variable refers to overall experience and proficiency in the construction industry. It was assessed through multiple choice questions regarding level of education, profession, expert area, as well as building phases and the size of building projects in which one is usually involved. Confidence levels within BR18 was also included in assessing this variable. This set of questions gave a detailed assessment of participants' extent of general knowledge in the subject matter area.

BIM expertise: An assessment of this variable was conducted by asking participants about their confidence in various BIM competences that are related to ARC workflows: *3D-modeling, IFC format exporting, collision control, visual programming, classification codes, data standards, and digital delivery of building models.* Participants rated their familiarity with each of the mentioned areas in a range from "Not at all Familiar" to "Very Familiar." Each choice had a value, which was used to determine each participants' overall competency score, where the highest score was fourteen and the lowest was negative fourteen.

Source experience: Source experience variability was assessed using two questions. Participants were asked about their familiarity and satisfaction with SMC. Answer options were given on a 5-point scale.

Availability of information: Manipulation of this variable occurred along the dimension of attributional abstraction. The 3D visualization was set to the same position for all scenarios. Two conditions were developed through altering information cues in the rule description windows, in such a way that the correctness of the information is preserved. In the third condition, the textual rule description was replaced by a window explaining the system's function only in parameters. Participants were assigned to the conditions randomly.

3.3 Dependent variables

Trust judgment: Trust judgements were measured by the percentage of participants who gave a positive answer to the question "Do you trust the information that you saw on the previous picture?".

Rationale to trust judgment: Participants were asked to reason their trust judgment. Answers were categorized into either of the three strategies proposed in the 3S-model. If multiple features were mentioned, the rationale was categorized according to the apparently dominant argument. Rationales that did not fall into any category were classified as "other." Each response was coded according to the definition of each trust strategy as described by Lucassen and Schraagen (2011).

4. RESULTS

In this section data collected from the experiment is analyzed and results are shown for each hypothesis. Furthermore, the chosen analysis methods are described along with the calculation procedure.

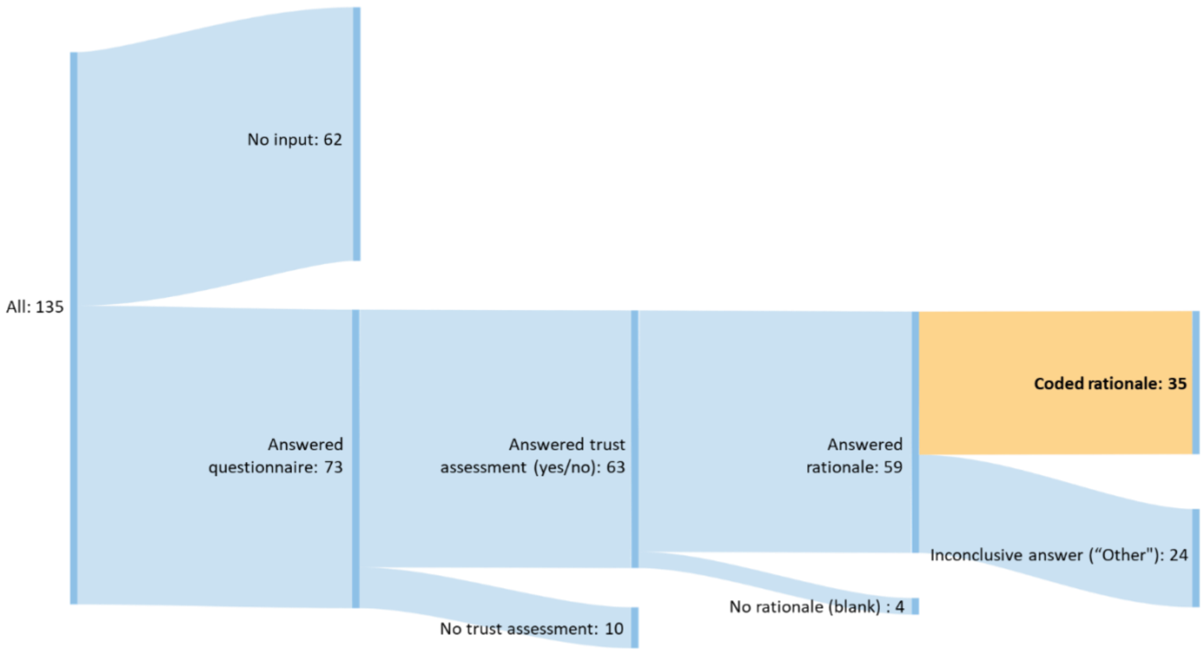

Fig. 3: Overview of respondents.

Of the 135 participants, 73 responses (54%) could be used for analysis. Of the responses 35 (26%) provided rationale for their trust judgments which could be categorized into one of the strategies framed by the 3S-model. Fig. 3 provides a summary of the distribution of the responses, where rationale responses (henceforth known simply as their trust strategy) could be classified as "semantic features", "source features", or "surface features". Participants were categorized according to similar criteria used by Lucassen and Schraagen (2011) for the original version of the 3S model, details of which are shown in Table 2.

Table 2: Criteria for categorization of participants into trust strategy groups.

Trust strategy	Criteria for categorization
Semantic	• Evaluates accuracy • Utilizes expertise* • Validates correctness • Finds meaning
Source	• Evaluates the author/creator • Seeks external validation (e.g. certification) • Makes judgement based on previous experience
Surface	• No evaluation of meaning holding content present • Utilizes information skills** • Describe what is shown without validating correctness
Other	• No clear indicators of thought process • Response was left blank/random key inputs were inserted without meaning • Averts providing reasons (e.g. stating personal opinions)

**In cases where the participant expresses lack of expertise, categorize as semantic anyway with the caveat that an unsuccessful attempt was made to use their expertise*
*** Information skills refers to "common sense" or a general idea, without expertise to rely on to make a validation.*

4.1 H1: Domain expertise can be identified by investigating the competencies of those who base their trust judgment on semantic features.

H1 hypothesizes that users which were categorized as using sematic features as part of their trust strategy can highlight similar characteristics among users within the group. According to the theory initial theory established by Lucassen and Schraagen (2011), domain experts utilize semantic features, so the question is not whether there are domain experts in the semantic group, but rather, what other common characteristics are present within the group?

To answer this question, the responses of the categorized participants (semantic-, source- and surface features trust strategy groups) were analyzed. The following observations were made:

Participants categorized into the semantic features group chose “Building Information Technology” (BIT) and “Engineering” as their areas of expertise more frequently than the source- and surface features groups combined.

Participants chose “Special Facilities (Hospitals, Schools, etc.)” with a significantly higher frequency across the entire sample. It was most frequently chosen by participants which were categorized into the semantic features group.

“Design” was chosen as the project phase most frequently across the entire sample (all three trust strategy groups) with significant percentages of both the semantic- and surface features groups choosing this option.

Across all three trust strategy groups, familiarity with most of the BIM competencies was high.

On average, participants within the semantic features group attained higher BIM competency scores than source or surface features groups.

Across all three groups, the BR18 score was low.

The following section explores these results, describes the statistical analysis methods used, and the statistical significance of the observations made.

For these observations to be analyzed, the data was collected into tables where the frequency with which each group chose specific responses to survey questions was recorded. The highest frequency for the choices was recorded for the trust groups responses (Table 3).

The probability that these outcomes occurred by coincidence was scrutinized with the use of 2x3 contingency tables and the Freeman-Halton extension of the Fishers Exact test. The groups (R_n) were designated as participants which chose a specific response or not, and the outcomes (C_n) were the trust strategy groups. Because this test is meant to determine if the relationship between trust strategy groups and the frequency with which each group made specific choices were significant, the null hypothesis was designated as “There is no significant relationship between trust strategy group and response choices.” Thirty-one contingency tables were created, one for each domain expertise-related question’s response choice, to investigate the null hypothesis. Two-tailed calculations were performed and the results for the second-tail p-values were also recorded in Table 3.

In the category “Area of Expertise", Building Information Technology (BIT) was the dominant choice for semantic features. The frequency of BIT being chosen within the semantic features group was 41% (n=17), the frequency in surface features 0%, (n=8) and source features, 30% (n=10). As a part of the whole sample however, BIT accounted for a 30% of the entire sample, with “Design” and “Other” accounting for 35% and 23% respectively of the sample. Despite the different ratios, the contingency tables showed that there was no significant relationship. Fig. 5 shows the p-values for “Other” which had a p-value closest to the critical p value.

The survey questions inquiring into “Project Size” and “Project Phase” were designed to identify common building project types in terms of scale, and the phase in which participants have the most experience. The responses in both questions were hypothesized as a characteristic where commonality among trust groups could be identified.

Within the experiment, “Special Facilities (Schools, Hospitals, etc.)” in Project Size and “Design” in Project Phase accounted for the most prominent choices among the semantic features trust group, and the most frequently chosen type across the entire sample. Of the 17 participants within the semantic features group, 41% (n=7) chose special facilities. “Design” was chosen most frequently across all three trust strategy groups with 63% (n=10) of the surface-, 59% (n=17) of the semantic-, and 40% (n=10) of the source features groups. It is important to note that for Project Size and "Project Phase" several participants across the three trust strategy groups chose "Other" and listed two or more of the provided choices as their response. Each choice for these questions were treated at mutually exclusive events and participants which chose "Other" but listed several of the already available choices were treated as "Other" responses.

Table 3. Collection of highest frequency for domain expertise related survey responses. Bold text show the most prominent responses within each subject area.

Survey Question Topic	Response Choice	Highest Frequency	Trust Strategy Group	P-value ($p \leq 0.05$)
Education	High School	NONE	NONE	NONE
	Technical School	NONE	NONE	NONE
	Bachelor	7	Semantic	0.271
	Master	**9**	**Semantic**	**0.190**
	Ph.D.	2	Source/Surface	0.123
	Other	1	Semantic	1.000
Profession	Architect	3	Semantic	0.429
	Architectural Technologist	**6**	**Semantic**	**0.739**
	Trade Worker	NONE	NONE	NONE
	Engineer	**6**	**Semantic**	**0.900**
	Leadership	1	Semantic	1.000
	Other	2	Source	0.545
Years of Experience	1 year or less	1	ALL	0.792
	2-5 years	4	Semantic/Surface	0.463
	6-10 years	4	Semantic	0.470
	10 years +	**8**	**Semantic**	**0.827**
Area of Expertise	**Building Information Technology**	**7**	**Semantic**	**0.121**
	Design	5	Source	0.386
	Leadership	2	Source	0.125
	Engineering	1	Semantic/Surface	0.714
	Other	5	Semantic	0.088
Project Phase	**Design**	**10**	**Semantic**	**0.616**
	Construction	2	Semantic/Source	0.545
	Both	3	Semantic	0.873
	Other	5	Semantic	0.088
Project Size	Low-Density Residential	2	Source	0.123
	High-Density Residential	4	Source	0.251
	Industrial	2	Semantic/Surface	0.682
	Special Facilities	**7**	**Semantic**	**0.050**
	Infrastructure	2	Semantic	0.792
	Other	2	Semantic	0.437

Fisher's Exact Test: Area of Expertise (Other)			
Null Hypothesis:	*There is no significant relationship between "Other" as an Area of Expertise choice and categorization into the Semantic Features Trust strategy group.*		
Outcomes (C_n)	**Group (R_n)**		**Total**
	Other	**NOT-Other**	
Semantic	5	12	17
Surface	3	5	8
Source	0	10	10
Total	8	27	35
	P-value: 0.088		
	$P_{critical}$: 0.050		

Fig. 4: 2x3 Contingency table for examining the relationship between Other as an Area of Expertise choice among Semantic- and Non-semantic features trust groups.

The Freeman-Halton extension was performed for all response choices in both the Project Size and Project Phase categories in the same fashion as it was performed for "Area of Expertise." "Special Facilities" (p=0.0501) for Project Size and "Other" (p=0.0877) for Project Phase were close to the critical p-value, however not statistically significant.

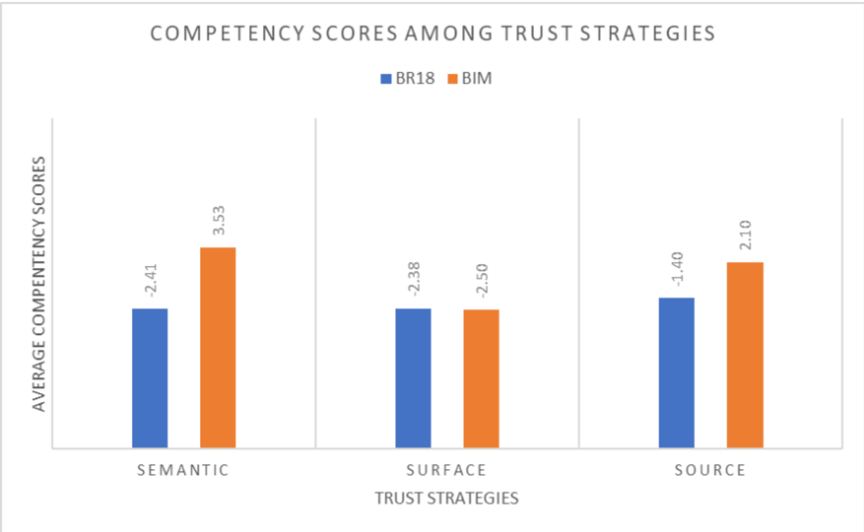

Fig. 6: Bar chart with Average BIM and BR18 competency scores for each trust strategy group.

The BIM competency score is based on seven competencies;3D modelling, IFC format exporting, collision control, visual programming, classification codes, data standards, and digital delivery of building models. These competencies were chosen based on their suspected relevance to ARC workflows. Based on H1, the 3S model can identify which of these competencies are common characteristics among domain experts and therefore confirm their relevance.

Participants across all three trust strategy groups (n=35) were most familiar with 3D modeling (51%,), IFC format exporting (40%), and collision control (37%). Less than 35% chose "Very Familiar" for the remaining competencies respectively. Within the semantic features group (n=17), similar patterns were observed with 3D modelling" having the strongest ratio (64%), followed by „IFC format exporting" (53%), and "Collision Control", "Classification codes", and "Digital delivery of building models" (all three tied with 47%).

2x2 contingency tables were created and the Fischers Exact Test was used to determine the statisical significance of the semantic features' choices. The null hypothesis was designated as "There is no relationship between competence familiarity and semantic features as the categorized trust strategy". The results revealed that there is no statisical significance (see Table 4).

Table 4: Collection of p-values for competences to determine their relevance to ARC workflows.

Comptence Subject	P-value ($p_{critical} \leq 0.05$)
3D modeling	0.1811
IFC format exporting	0.1756
Collision Control	0.0858
Visual Programming	1.0000
Classification Codes	0.1642
Digitial delivery of building models	0.1642
Data standards	0.7245

The BIM and BR18 competency scores were scores created to determine participants competency level in BMC related BIM skills, and BR18 regulations related to the software used in the experiment. Participants scores in each competency category (BIM and BR18 respectively), could be highest fourteen or lowest negative fourteen, with the average range residing between seven and negative seven. On average, each trust strategy group's BIM score was within the average range, with the semantic features group scoring higher than surface- and source features. BR18 scores across all three groups were lower than BIM scores, with the average score in the negative ranges (Fig. 6). The likelihood of these averages occurring by chance was scrutinized with a two-tailed, one sample t-test. The T-tests were used to calculate the expected variability of the normally distributed data set and establish the significance of the score's distribution among the trust strategy groups. For the t-test the research question was "Is the average for the competency score greater than zero?" for BIM competency scores, and "Is the average for the competency score less than zero?" for BR18 scores. For both cases the null value, or the expected mean was set to zero. The t-test determined that BIM scores had no statistical significance (p=0.246), however, the BR18 scores show significant statistical significance (p=0.024).

3x3 contingency tables were also created to determine the significance of the relationships between BIM and BR18 scores and the group with which the participants were categorized into. The Groups (R_n) were designated as the three trust strategy groups (Semantic-, Source-, and Surface features), and the Outcomes (C_n) were the quartiles for the competency score (below average, average, and above average). The null hypothesis was designated in a similar fashion to previous contingency tables: "The relationship between trust strategy group and competency score is not significant." The Freeman-Halton extension of the Fisher's Exact Test was performed, and the results indicated no significance for BIM competency scores (p=0.399) and BR18 scores (p=0.509).

The analyses performed for H1 examined the individual survey questions and their relationship to the trust strategy groups with null hypothesis declaring that the observed outcomes were statistically insignificant. While some of the results established relationships between specific characteristics and domain experts, it is too weak to validate H1 and the null hypothesis is therefore accepted.

4.2 H2: Positive or negative source experience prior to interaction influences the development of trust positively or negatively respectively.

The second hypothesis was analyzed by using Fisher's exact test, a non-parametric association test between two sets of dichotomous data. The test compares observed data to a calculated prediction, in order to determine if the result from the observation is due to chance or due to the speculated relationship between the variables. By implication, the null hypothesis is formulated as follows: "The trust judgement does not differ along the dimension of prior source experience."

The first variability was participants' pre-existing attitude towards Solibri Model Checker, which was coded as either "positive" or "negative." Respondents, who were neither satisfied nor dissatisfied with the software (neutral option) were excluded from this calculation. The trust assessment was the second variability, which could be answered with "yes" or "no."

#1 Limitations:
- Q 12. (contentment with Solibri): exclude ”neutral option”
- Q 14. (trust assessment): exclude ”no answer”

		Trust assessment		
		Yes	No	
Source Experience	Positive	18	5	23
	Negative	3	3	6
		21	8	Σ= 29

Fischer`s Exact Test:	**0.3045**

#2 Limitations:
- Q 12. (contentment with Solibri): exclude ”neutral option”
- Q 14. (trust assessment): exclude ”no answer”
- Q 11. (familiarity with Solibri): exclude “not at all familiar”

		Trust assessment		
		Yes	No	
Source Experience	Positive	18	5	23
	Negative	1	2	3
		19	7	Σ= 26

Fischer`s Exact Test:	**0.1669**

#3 Limitations:
- Q 12. (contentment with Solibri): exclude ”neutral option”
- Q 14. (trust assessment): exclude ”no answer”
- Q 11. (familiarity with Solibri): exclude “not at all familiar”, ”not very familiar”

		Trust assessment		
		Yes	No	
Source Experience	Positive	17	4	21
	Negative	1	2	3
		18	6	Σ= 24

Fischer`s Exact Test:	**0.14**

#4 Limitations:
- Q 12. (contentment with Solibri): exclude ”neutral option”
- Q 14. (trust assessment): exclude ”no answer”
- Q 11. (familiarity with Solibri): exclude “not at all familiar”, ”not very familiar”, ”quite familiar”

		Trust assessment		
		Yes	No	
Source Experience	Positive	11	3	14
	Negative	0	2	2
		11	5	Σ= 16

Fischer`s Exact Test:	**0.08**

Fig. 7: Source experience and trust assessment

Another limitation, source familiarity was introduced to the analysis in order to measure the impact of users´ amount of experience on the hypothesized relation. Participants rated their familiarity with Solibri Model Checker on a 5-point Likert scale, where the lowest end is “0” (not familiar at all), and the highest rating is “5” (very familiar). The limitation was applied in a progressive manner, starting from no limitation to filtering out users with ratings from “0” upwards. As a result, four calculations were performed along this dimension, as illustrated in Fig. 7. The calculation could not be continued after the third round of the latter limitation as a consequence of data scarcity.

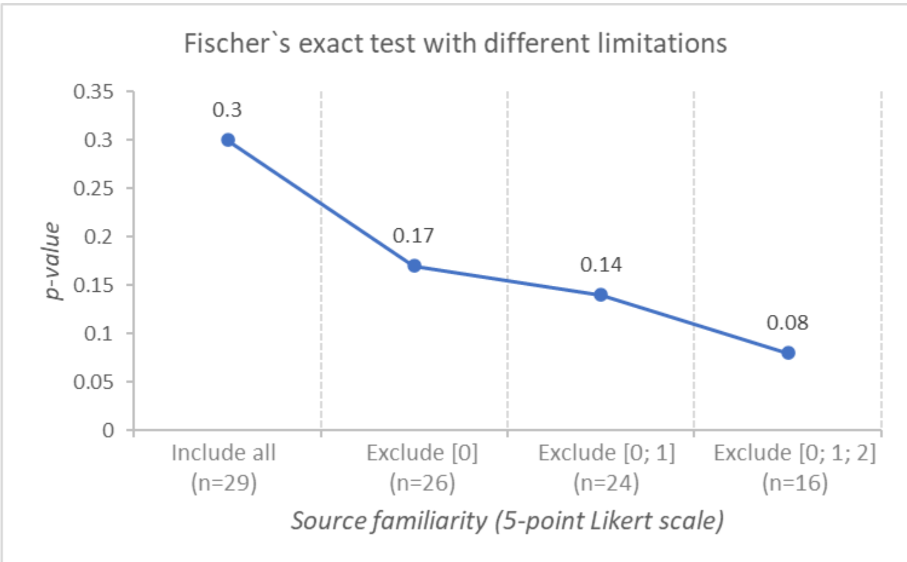

Fig. 8: Fischer´s exact test with different limitations

The findings suggest that there was no statistically significant association ($p < .05$ = not significant) between the participants’ source experience and their trust judgment, in either of the four calculations: ($p = 0.3045$; $n = 29$), ($p = 0.17$; $n = 26$), ($p = 0.14$; $n = 24$), ($p = 0.08$; $n = 16$). Therefore, H2 is rejected, and the null hypothesis is accepted: pre-existing source experience does not influence the development of trust in the current interaction.

4.3 H3: Adding to the displayed information along the dimension of attributional abstraction will not expand the range of users in either of the trust strategies.

Three conditions were set up in accordance with H3, wherein information features were manipulated along the dimension of attributional abstraction (see Table 1, Fig. 1 and Fig. 2). Each participant was assigned to one randomly selected condition. Out of 35 people who fully completed the survey, and whose trust rationale could be categorized, Condition 1 was assigned to 12; Condition 2 to 11; and Condition 3 to 12 participants (Fig. 4).

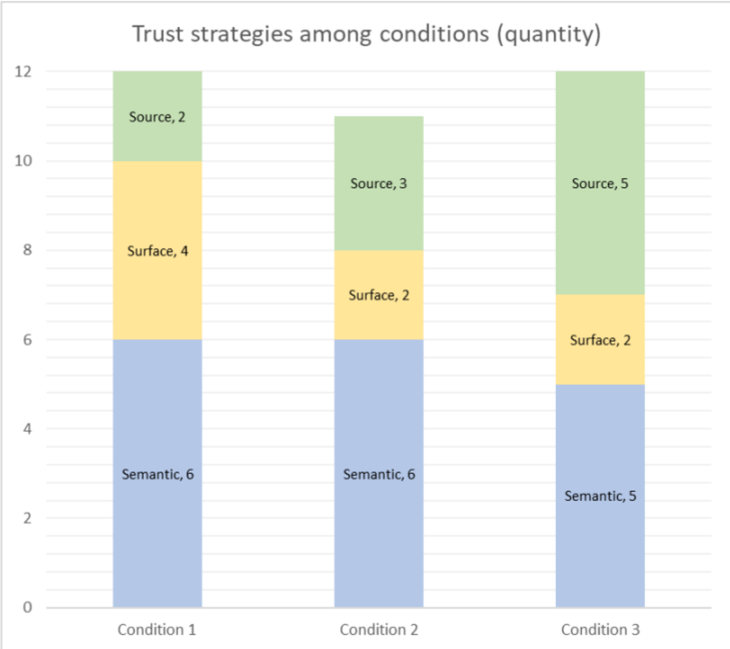

Fig. 5: Trust strategies among conditions (quantity)

Regarding the results, approximately half of the participants chose the semantic strategy consistently through all conditions. The remaining participants reasoned their trust judgements with either surface or source information features. There was some fluctuation in the ratio of these groups' size between the conditions: participants picked between surface and source features impartially in case of Condition 2, whereas surface trust strategy was more favorable with Condition 1, while surface features was preferred with Condition 3.

The Freeman-Halton extension of Fisher's exact probability test (Freeman and Halton, 1951) was performed in order to determine whether the observed array of frequencies in each trust strategy group by condition is due to chance (hypothesis) or due to the influence of the independent variable (null hypothesis). Data was input into a 3x3 contingency table, thereafter the result of the calculation ($p = 0.73$; $n = 35$) suggests no significant difference between the observed array and any random one. Hence, the statistical result rejects the null hypothesis and accepts H3.

5. DISCUSSION

5.1 H1

The first hypothesis attempts to determine the 3S-model's ability to identify common characteristics among domain experts. This section interprets the results and draw conclusions from the observed outcomes.

The results show that the responses from participants point to common characteristics based on the number of participants collected into the same response category. Examples such as "Building Information Technology (BIT)" from the "Area of Expertise" question show that inquiries into expertise are relevant. The "Other" category within this question had more statistical significance (albeit not enough to reach the critical margin) than BIT, which had more participants which chose it. This implies that perhaps there are other fields of expertise that were not named which might be more relevant than BIT. The same pattern repeats with variation on the statistical significance throughout the remaining five questions, with "Project Size" being the only question which had a result close to statistical significance. With a p-value of 0.0501, “Special Facilities (schools, hospitals, etc.)” was the preferred choice for Project Size across all three trust strategy groups. Given that often special facility projects are large, complex, and have strict requirements, it comes as no surprise that domain experts would choose this project type. BMC solutions would frequently be a vital component of these kind of projects and explains why domain experts in particular, obtained their expertise from these projects. Falling short of statistical significance is likely attributed to the small sample size, and a larger sample size could strengthen these claims.

The competency scores rank participants according to their confidence ratings on a 5-point Likert scale for various aspects of BMC model checking and BR18. The scores were low in both categories with the majority of participants rating themselves in the average range (a total score between -7 and +7). Despite this, the average score for each trust strategy group supported Lucassen and Schraagen’s (2011) claim: domain experts have the skills and knowledge to examine the semantic elements relevant to a trust judgement. BIM competency scores were highest in the semantic features group, and lowest in the semantic features group (Fig. 6). It was unexpected that the source features group scored higher in BIM competency than surface features. Lucassen and Schraagen stated with regards to the source features category that “limited domain expertise (of novices) … and limited information skills (of both novices and experts; Walraven et al., 2009) might have been the cause of the observation that users solely rely on previous experiences with the source.” This contradicts the observations found in the BIM competency scores. However, Gade and Svidt (2021) hypothesized that users often spend more time scrutinizing a system when the inner workings are of interest. The source features anomaly is likely the passive evaluation of professionals which are not interested in the workings, but instead seek validation from previous experiences or external sources (reputation, certification from authority figure, etc.) that the system works. The validity of this contemplation requires further investigation as the data from this study is insufficient to confirm or deny these claims.

The 3S-model may have the potential to identify common characteristics, however in this study, the data is insufficient to claim this finding with any prominent level of confidence. What can be said with confidence, on the other hand, is that across all three trust strategy groups, the average BR18 competency score is exceptionally low. The results of the t-test proves that the BR18 score, and trust strategy group have no relationship to one another. The likely explanation for this outcome is the availability of BR18 online and in print. Anyone with access to the internet, a public library, or a bookstore can gain access to the Danish Building regulations in its fullest, which eliminates the need for memorizing or acquiring experience in this area. The outcome establishes that user expertise (knowledge) of Danish Building regulations is an irrelevant factor of trust in ARC.

H1 was considered inconclusive because the majority of outcomes had no statistical significance. The source features group consistently had higher outcomes in all questions than the semantic features group despite the original theory stating that source strategies are used when both domain expertise and information skills are limited (Lucassen and Schraagen, 2011). Further investigation is required to determine the source of the anomaly within the semantic features group, which is suspected to be a unique characteristic of AEC professionals to defer to other sources (particularly authoritative figures) for validation.

5.2 H2

The second hypothesis suggested that initial impression of the source can prognose a bias towards trusting or distrusting the system in forthcoming evaluations. Although the data fell short from proving significant dissimilarity from any incidental pattern, the results indicate a tendency towards the hypothesized outcome.

Firstly, participants were progressively excluded from the quantitative association test based on their amount of experience with the program (Fig. 7). This manipulation resulted in increasing association between the users` opinion on the source and their trust evaluation`s outcome. This finding aligns well with the study of Hilligoss and Rieh (2008), one of the theories upon which the 3S-model was built. They investigated source-related heuristics, which is a credibility assessment strategy which comes into play when the user has so much positive or negative experience with the source, that semantic or surface cues are diminished or ruled out during the evaluation. The observed pattern indicates that the amount of experience one has with a particular source is proportional with the degree of influence an opinion has on the actual trust development. In other words, the more one has experienced with the source, the stronger opinion he/she has about its trustworthiness, which can generate a positive or negative bias towards the source at the next instance when it must be judged. However, it is important to mention that the data collected during the study cannot quantitatively confirm the truthfulness of the present contemplation.

Secondly, Fig. 8 shows the biggest drop in p-value between the first and second calculation. The first calculation set no limitation to source familiarity, whereas the second one excluded those who never met with Solibri Model Checker. Presuming that the group of participants excluded from the second calculation answered arbitrarily to the question about their opinion on the program (because they had no initial experience that they could reach back to), the drop in p-value suggests that an opinion based on a personal whim is a significantly weaker factor during a trust judgment, than an opinion formed upon any background knowledge. The circular nature of experience during trust evolution was identified in both the integrated model of trust in information (Kelton et al., 2008) and the conceptual model of the dynamic process that governs trust and its effect on reliance (Lee and See, 2004). This finding indicates the weights of pre-existing experience in different amounts as a factor in trust evolution.

5.3 H3

In the case of determining the influence of the displayed information explaining the system on users` trust formation behavior, the findings suggest no significant effect on which trust strategy participants pick upon evaluating the system`s capabilities. However, some association between the occurrence of different information features and the present participant pool`s trusting nature can be interpreted through the observed patterns.

Firstly, the shift in the balance between the surface and source trust strategy groups` size can be brought into relation with the amount of natural language in each condition. Surface strategy dominated at Condition 1, where natural text describing the system´s purpose was emphasized. Source strategy was most popular at Condition 3, where the natural text was replaced by a window showing parameters. The proportion of the two strategies were the most balanced at Condition 2, where all information features from the two conditions were present on the display.

According to Lee and See (2004), the mere availability of information does not necessarily enhance the appropriateness of trust, as it also depends on how information is presented: the description must be formatted in a manner which supports different means of information assimilation (analytic-, analogical-, affect-based). In the context of the 3S-model, the way information is introduced may invite users to process systematically (e.g., in case of Condition 1, where the mechanism is promptly explained in sentences), or turn them to a passive evaluation (source trust strategy) when the surface-type information cues require too much processing for comprehension (e.g., Condition 3, where the perceiver has to make sense of the system`s logic based on a table, and without the help of any explanatory sentence).

Interestingly, the range of users choosing the semantic trust strategy remained steady regardless of the manipulations. The phenomenon that adding more information to the display about the system`s workings did not motivate more people to study the meaning-holding components (semantic trust strategy), can be interpreted into correlation with Gade and Svidt`s (2021) findings: construction specialists (e.g., engineers) generally would not attempt to understand the BMC system completely, for being able to scrutinize the underlying mechanisms in detail might overburden their workflow. They would instead place their trust in the developer or in the authority that is responsible for the system`s implementation. In turn, findings suggest that people who are interested in the system`s explicit procedure, will study the information regardless of the form in which it is displayed.

5.4 Limitations and further research

Many limitations were revealed in the course of the study. This section collects all identified issues in a structured manner, as well as suggestions to overcome or avoid them in the future. Further research ideas are also proposed.

Primarily, the amount of people participating in the experiment were few for quantitative research such as this study. Observations made on small data cannot substantiate deep-seated arguments, since observed patterns have weak statistical significance and can be difficult to distinguish from random occurrences. The small respondent group can arguably be reasoned by the narrow selection pool that was set for the experiment. In possible further research, we would expect a higher involvement rate if the experiment were conducted in English language, and with the use of a ruleset that is attainable for AEC professionals internationally (i.e., avoid country-specific regulations).

Regarding the experiment design, the system was presented to participants by screenshots, for direct interaction was not feasible in the chosen composition. Showing static images instead of a working system compromised or even removed several surface features, e.g., rotate/zoom 3D visualization, interact with tabs and windows, scroll text, etc. Lack of interaction could also demotivate participants from taking the experiment seriously or from continuing altogether. To overcome this limitation, we suggest changing from online surveys to personal meetings, where it is possible to guide participants along the experiment. One-on-one meetings can furthermore enable the researcher to consider situational factors that have an influence on trust behavior (see Hoff and Bashir, 2015), and investigate their significance in relation with the 3S-model. Furthermore, the amount of time spent on the experiment could further reflect participants' interest. Attempts were made record time used on the questionnaire through the survey platform, however the collected data proved to be too inconsistent; For example, participants did not finish the questionnaire (they did not click the "Finish" button) or left the window open for extended periods of time (more than 24 hours). Should time be included in a replication of this experiment, it is recommended that it be controlled more strictly, within in the data collection platform or via a third party application.

The wording of the questions had substantial importance throughout the experiment. For example, participants were asked to "rate their familiarity" with the source program, however this question can be interpreted in more than one way. Familiarity does not necessarily mean firsthand experience with the system, as it can also include knowledge assimilated from advertisement, gossip, or reputation. We suggest in further research to differentiate variabilities along several types of familiarities, to measure the impact levels of pre-existing personal experience and pre-existing knowledge from an external source.

The source features group behaved in ways inconsistent with the theories of the 3S-model, which requires further investigation. Factors such as situational factors (which were not examined in this study), the experimental design, or the unique characteristics of AEC professionals could explain why source features were the second most prominent group in the study. Confirmation of this claim through modification of the experimental design with the previously mentioned recommendations could confirm the unique behavior if it exists.

6. CONCLUSION

The study`s purpose was to investigate the slow progress of automation implementation in the AEC industry from a socio-technical point of view. The 3S-model theory from the field of cognitive psychology was adapted to study industry participants` trust behavior. The theory`s original experiment was modified into context, which, by the help of three hypothesis questions, meant to shed light on the main research question: *What is the significance of different information features, and pertaining user characteristics on human-automation trust behaviors in the domain of Automatic Rule Checking?*

The findings show no significant correlation between trust behavior and the user-characteristics assumed in this study. Domain experts can spread over diverse levels of education, years of experience, professions, expert areas, and project phases. The most indicative user-characteristic that gathered domain experts, however, was their work experience with special facility projects. Given that such projects usually require a rather sophisticated use of BIM, it illustrates that expertise in ARC technology can be obtained by merely being exposed to it.

Furthermore, the results identify two types of users based on their preferred information features. One group of people tend to seek semantic cues regardless of the fashion in which information is displayed, supposedly because they are interested in understanding the inner workings in detail. The other group`s concern is more about that the automation works, and less about how it works. Their trust behavior therefore can be influenced by the presentation method because they either utilize surface- or source features, based on which one of them gains more prominence in the situation.

Further studies are required to refine and broaden the model`s application in this domain, for which recommendations were addressed upon the lessons drawn from this experiment. The 3S-model can be used to test correlation between user characteristics and information features. Understanding these drivers of trust in regards to ARC can benefit the absorption of such technology in the AEC industry. The significance lies in designing software to appropriate trust for the sake of appropriate use.

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