Antecedents of Organizational Agility During Business Uncertainty in Noninformation Technology Sectors

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ABSTRACT

The prolonged COVID-19 pandemic, economic stress, and geopolitical tensions have caused market disruptions and other forces that have likely increased organizational agility. This article focuses on the antecedents of organizational agility under such business uncertainty in the noninformation technology (IT) sectors. The research model stems from the uncertainty reduction theory and the following three frameworks: (1) dynamic capabilities; (2) decision making; and (3) business intelligence and analytics (BI&A) competitive advantage maturity model. It considers intelligence (risk and opportunity) and aligned decision making as agility predictors. It lists employee capability and IT flexibility as antecedents of intelligence, aligned decision making, and organizational agility. The results indicate that employee capability affects agility through the mediating variables of intelligence and aligned decision making. IT flexibility impacts agility only through intelligence. Both intelligence and aligned decision making have significant direct effects on agility.

KEYWORDS

Analytics, Decision-Making, Dynamic Capabilities, Employee Capability, Intelligence, IT Flexibility, Opportunity, Risk

INTRODUCTION

Uncertainty evoked by extreme events can result in a marked increase in agility needed to address environmental threats (Teece, 2007; Teece et al., 2016). A pandemic, economic stress, financial market volatility, geopolitical tensions, and other emergencies necessitate intelligence-assisted solutions (He et al., 2021; Shiau et al., 2021). COVID-19 is an example of an extreme event. There is anecdotal and research evidence that nontechnology companies adapted by embracing digital practices (Ågerfalk et al., 2020; Kamal, 2020). The investigation did not directly link with COVID-19; however, its severe effects provided a backdrop for studying organizational agility. The study focused on using intelligence and decision-making skills rather than developed information systems. Information technology (IT) companies, which typically have experience with agility, were excluded from this research. In the systems development area, researchers and practitioners have focused on agile software development (Knaster & Leffingwell, 2020; Siau, Woo, et al., 2022). Nontechnology sectors routinely
use intelligence, including artificial intelligence (AI, George et al., 2020; Hyder et al., 2019; Wang & Siau, 2019).

Chen and Siau (2020) demonstrated that business intelligence and analytics (BI&A) and IT infrastructure positively impact organizational agility. Further research is encouraged on the interaction between the antecedents and the factors that influence BIA. The response to environmental uncertainty evokes the following research questions:

- What are the antecedents of organizational agility in nontechnology sectors?
- What are the relative strengths of factors that determine organizational agility?

The research purported to establish quantitative measurements of the elements, whereas past literature has primarily taken a qualitative approach.

This article’s research examines the interplay among intelligence, decision making, employee capability, and IT flexibility as antecedents of organizational agility. The severe impacts of COVID-19 surfaced in March 2020. The author speculated that companies initiated or effectuated changes in their business practices within four months. Therefore, survey data was collected from 136 respondents in June 2020.

BACKGROUND

COVID-19 caused substantial disruptions in how companies transacted business, governments managed health, monetary, and fiscal policies, and people worked, studied, and lived (Ivanov, 2020; Moon, 2020; Xie et al., 2020). Although most technology companies fared well, some nontechnology sectors had difficulty managing the pandemic’s impact (Grover & Sabherwal, 2020; Kim, 2020). Negatively impacted nontechnology areas included the retail, restaurant, transportation, and hospitality sectors (Bartik et al., 2020; Gössling et al., 2020; Kim, 2020). Still, many companies did improve their home-delivery processes (Kim, 2020), governments changed their service modes (Gabryelczyk, 2020), healthcare providers altered their systems (Ohannessian et al., 2020), and universities delivered flexible course modes (Zou et al., 2020). Companies gathered information on risks and opportunities, assessed the cost-benefits of proposed changes, made rapid decisions, and took steps to effectuate change (Kamal, 2020).

Software development companies routinely employ agility-based approaches to project complexity and dynamism (Beard et al., 2022; Butler et al., 2020; Siau, Woo, et al., 2022). Nonsoftware companies can also use agile project management practices (Conforto et al., 2014). Several nonIT sectors use AI practices, including mining, self-driving vehicles, education, manufacturing, human resources, military, healthcare, accounting, and finance (Hyder et al., 2019; Siau, Nah et al., 2022; Wang & Siau, 2019). Digitalization is advancing in manufacturing, service, aviation, operations and supply chain, retail, tourism, higher education, government, police, and transportation (Kamal, 2020).

In the case of the COVID-19 jolt to the business environment, organizational agility became necessary for surviving and thriving. Many nontechnology companies effectuated agility practices. The crucial agility antecedents included risk and opportunity intelligence, aligned decision making, employee capability, and IT flexibility. While prior literature took a qualitative approach, the current study takes a quantitative approach. The research explored the following:

- What are the antecedents of organizational agility in nontechnology sectors?
- What are the relative strengths of factors that determine organizational agility?

This article describes the framing of the research model from literature, measurements of constructs, hypotheses, methodology, reliability and validity, results, discussion, and conclusion. The Appendix provides the questionnaire.
FRAMING THE RESEARCH MODEL

Uncertainty is a lack of understanding and awareness of issues, events, paths to follow, or solutions (Kramer, 1999; PMI, 2021). Business uncertainty has become more pronounced because of pandemic, geopolitical, financial, and economic risks. Researchers have emphasized organizational agility in responding to uncertainty hazards (Gabryelczyk, 2020; Knaster & Leffingwell, 2020; Tilman, 2019). Uncertainty reduction theory suggests that when organizations experience uncertainty, they seek information to manage the consequent risks (Kramer, 1999). Conversely, disorganized information that provides no insight can increase uncertainty (Planalp & Honeycutt, 1985). Intelligence is the ability to process information and knowledge to gain insight into a complex environment (Nakashima, 1999; Sejnowski, 2018; Tilman, 2019). As the MaCuDe Report recommends, decision-making strategies and tactics can employ intelligence data and associated technologies to achieve organizational transformation (Lyytinen et al., 2021). This study hypothesizes that organizations will seek intelligent information on opportunities and risks for making quality decisions and choices to achieve organizational agility. Thus, agility has intelligence and aligned decision making as direct antecedents.

George et al. (2020) presented the BI&A competitive advantage maturity model by employing factors like information, technologies, infrastructure, processes, participants, customers, environment, strategic alignment, and products/services. This study uses employees instead of participants, intelligence instead of information, and specific industries instead of products/services and environment. It combines technologies, infrastructure, and processes into technological flexibility. The construct-aligned decision making includes item strategy, which implicitly contains customer emphasis. The construct IT flexibility consists of technology, infrastructure, and processes in an uncertain environment. Thus, employees and IT flexibility are direct antecedents of agility, intelligence, and aligned decision making.

The study’s research model stems from the uncertainty reduction theory (Kramer, 1999) and the following frameworks: (1) dynamic capabilities (Teece, 2007; Winter, 2003); decision making (Simon, 1960); and (3) BI&A competitive advantage maturity model (George et al., 2020). The dynamic capabilities framework focuses on sensing and seizing opportunities (Teece, 2007; Teece et al., 1997). The cost-benefit emphasis in fostering dynamic capabilities requires decision-making skills (Winter, 2003). Simon’s (1960) proposed decision-making framework includes intelligence, model, choice, and implementation (Pomerol & Adam, 2006). With the advent of analytics and deep learning (Berente et al., 2021; Sejnowski, 2018), intelligence has become vital for agility. This study treats it as a separate construct.

Intelligence is a higher-order construct composed of risk and opportunity intelligence (Tilman, 2019). The study measures intelligence in seven vital nonIT sectors. The second construct, aligned decision making, refers to the decision-making process while considering strategy, mission, values, and management and employee relationships. Prospect theory asserts that humans weigh loss more than gains (Kahneman & Tversky, 1979). Tversky and Kahneman (1991) argued that decision makers exhibit loss aversion by favoring the status quo to protect past decisions. Alignment between strategy, mission, and values and between management and employees should mitigate such problems. Transparency, trust, learning, and tolerance should improve decision making (Knaster & Leffingwell, 2020; Larman & Vodde, 2016). In this research, intelligence, measured by 14 indicators, and aligned decision making, measured by six indicators, serves as the direct antecedents of agility.

Employee capability incorporated agile development indicators like job competency, interpersonal skills, and motivation (Batra et al., 2016; Bick et al., 2018; Knaster & Leffingwell, 2020; Niederman et al., 2018). IT capability improves organizational agility (Lu & Ramamurthy, 2011). The research does not directly employ the construct IT capability. Instead, it uses IT flexibility to reflect the multiple modes of work caused by the pandemic, as well as the need for flexible processes and architectures (Zhang et al., 2009).
OPERATIONALIZATION AND MEASUREMENT

Teece et al. (2016) linked organizational agility with dynamic capabilities in the context of risk, uncertainty, and strategy. This section operationalizes and discusses the vital constructs employed in the study. Table 1 provides a list of relevant references.

Agility

The study operationalizes agility as detecting, assessing, and responding to changes in the business environment (Chen & Siau, 2020; Conboy, 2009). The underlying agility notion is derived from the dynamic capabilities framework. Teece (2007) operationalized dynamic capabilities as the capacity to: (1) sense and shape opportunities and threats; (2) seize opportunities; and (3) maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise’s intangible and tangible assets. Overby et al. (2006) defined enterprise agility as a firm’s ability to sense and respond to environmental change.

Risk and Opportunity Intelligence

The current study operationalizes intelligence as the capacity to process information in a complex environment for mitigating risk and enhancing opportunities. Empirical research has shown that business analytics and intelligence improve organizational agility (Chen & Siau, 2020). A firm needs robust market intelligence to track competitors’ actions, consumer preference changes, and economic shifts in business, manufacturing, healthcare, mining, and other areas (Nakashima, 1999; Tilman, 2019; Wang & Siau, 2019). AI developments and data science provide evidence that one can gather risk/opportunity intelligence in the biosphere, financial, political, technological, and regulatory, which affect all companies (Kelleher & Tierney, 2018; Tilman, 2019).

Aligned Decision Making

The current study operationalizes aligned decision making as modeling and implementing choices by alignment with organizational strategy, mission, and values. Effective decision making requires alignment between strategy and mission, leadership unity, trust between superiors and subordinates, and transparency (Doz & Kosonen, 2010; Goldman et al., 1995). The study emphasizes transparency and trust between supervisors and subordinates (Knaster & Leffingwell, 2020). In doing so, decision makers can implement measures with maximum information availability and less fear (Batra et al., 2016).

Transparency of shared data supports the decision-making process because managers can gain a holistic view and relate various information sources (Knaster & Leffingwell, 2020). People close to the situation should make the decisions, necessitating managers to trust their staff (Fowler & Highsmith, 2001).

Employee Capability

Research defines employee capability as the competencies that enhance job performance and foster adaptiveness essential for organizational transformation and success. Agile practices emphasize employee capability, such as building projects around motivated individuals, providing individuals with a supportive work environment, and trusting individuals to fulfill their responsibilities (Baljepally et al., 2017; Boehm & Turner, 2004; Fontana et al., 2014; Fowler & Highsmith, 2001). Employee competencies in agile software development include technical skills, business domain knowledge, interpersonal skills (Batra et al., 2016), motivation (Fowler & Highsmith, 2001), and coordination skills (Bick et al., 2018; Dietrich et al., 2013; Dingsøyr et al., 2018). Turbulent environments require employee flexibility skills for achieving dynamic capabilities (Bhattacharya et al., 2005). Such skills include adaptability (Beltrán-Martín & Roca-Puig, 2013), creativity (Camps et al., 2016; Conforto & Amaral, 2010), resilience, and the ability to adapt in the face of stress and adversity (Wu et al., 2013).
| Constructs                          | Key Sources                                                                 |
|------------------------------------|-----------------------------------------------------------------------------|
| Agility                            | (Chen & Siau, 2020; Conboy, 2009; Helfat & Peteraf, 2015; Overby et al., 2006; Teece, 2007) |
| Detect                             | (Chen & Siau, 2020; Conboy, 2009; Teece, 2007)                              |
| Assess                             | (Conboy, 2009; Teece, 2007)                                                |
| Respond                            | (Chen & Siau, 2020; Conboy, 2009; Teece, 2007)                              |
| **Risk and Opportunity Intelligence** |                                                                               |
| During Uncertainty                 | (Overby et al., 2006; Teece, 2007)                                         |
| During Stability                   | (Overby et al., 2006; Teece, 2007)                                         |
| Financial                          | (Overby et al., 2006; Tilman, 2019; Wang & Siau, 2019)                      |
| Political                          | (Overby et al., 2006; Tilman, 2019)                                         |
| Biosphere                          | (Kamal, 2020; Tilman, 2019)                                                |
| Technological                      | (George et al., 2020; Tilman, 2019)                                         |
| Regulatory                         | (Tilman, 2019; Wang & Siau, 2019)                                          |
| **Aligned Decision Making**        |                                                                             |
| Align Strategy-Mission-Values      | (Bhushan & Rai, 2007; Knaster & Leffingwell, 2020; Tilman, 2019)            |
| Align Management-Employees         | (Fowler & Highsmith, 2001; Knaster & Leffingwell, 2020)                    |
| Transparency                       | (Knaster & Leffingwell, 2020; Larman & Vodde, 2016)                         |
| Tolerance                          | (Storme et al., 2020; Weinzier & Esken, 2017)                               |
| Trust                              | (Knaster & Leffingwell, 2020; Storme et al., 2020)                         |
| Learning                           | (Knaster & Leffingwell, 2020; Larman & Vodde, 2016)                         |
| **Employee Capability**            |                                                                             |
| Job                                | (Batra et al., 2016; Beltrán-Martín & Roca-Puig, 2013; Boehm & Turner, 2004; Clark et al., 1997; George et al., 2020) |
| Interpersonal                      | (Batra et al., 2016; Camps, Oltra, Aldás-Manzano, Buenaventura-Vera, & Torres-Carballo, 2016) |
| Motivated                          | (Beltrán-Martín & Roca-Puig, 2013; Misra et al., 2009)                     |
| Coordination                       | (Bick et al., 2018; Feller et al., 2008)                                    |
| Adaptive                           | (Balijepally et al., 2006; Beltrán-Martín & Roca-Puig, 2013; Camps et al., 2016; Dingsoyr et al., 2012) |
| Creative                           | (Balijepally et al., 2006; Camps et al., 2016; Misra et al., 2009)         |
| Resilient                          | (Duckworth et al., 2007; Wu et al., 2013)                                   |
| **IT Flexibility**                 |                                                                             |
| Rapid Switching                    | (Chen & Siau, 2020; George et al., 2020; Lu & Ramamurthy, 2011)             |
| Hardware Primary                   | (Chen & Siau, 2020; Conger, 2020; Gabryelczyk, 2020)                        |
| Hardware Remote                    | (Chen & Siau, 2020; Conger, 2020; Kamal, 2020)                              |
| Connectivity                       | (Chen & Siau, 2020; Conger, 2020; Lu & Ramamurthy, 2011)                   |
| Processes Primary                  | (Athey & Schmutzler, 1995; George et al., 2020; Lu & Ramamurthy, 2011)     |
| Processes Remote                   | (Conger, 2020; George et al., 2020; Kamal, 2020)                            |
IT Flexibility

IT flexibility is operationalized as the ability of IT hardware, software, connectivity, and processes to adapt to business environment changes and geographic location. Nontechnology sectors have a fair degree of automation in business processes. The company must adjust information-dependent workflow and procedures if a pandemic, fire, hurricane, or earthquake force employees’ remote relocation (Shiau et al., 2021). Furthermore, the workplace is witnessing revised norms with both the office and home as common locations. Accordingly, employees need the proper hardware and connectivity from the new sites. Infrastructure and value-creation IT facilities should be accessible and adequate from both primary and remote workplaces (Conger, 2020; Han et al., 2017; Zhang et al., 2009). Infrastructure issues include hardware, connectivity, and compatibility (Zhang et al., 2009). Value-creation deals with workflow and processes (Athey & Schmutzler, 1995).

HYPOTHESES

A structured equation research model assembled the constructs described in the previous section. For clarity and comprehensiveness, Figure 1 shows the model using named codes for the indicators; later, the manuscript employs abbreviations. The figure corresponds to the questionnaire in the Appendix. Aligned decision making and intelligence are direct antecedents of agility. Intelligence is a second-
order construct composed of opportunity and risk intelligence. Employee capability and IT flexibility affect agility directly and through mediating variables aligned decision making and intelligence.

The researcher employed SmartPLS version 3 software (Ringle et al., 2015) to analyze the research model based on partial least squares for a structural equation modeling (PLS-SEM) approach (Richter et al., 2015). The researcher would select PLS-SEM if the goal is to predict key target constructs or if the research is exploratory or an extension of an existing structural theory (Gefen et al., 2000; Hair et al., 2016; Vinzi et al., 2010). Conversely, if the goal is theory testing, theory confirmation, or comparison of alternative theories, the researcher would select CB-SEM. In this study, the research is exploratory. It aims to predict agility. The research model implies the hypotheses listed in Table 2 and Figure 1.

**METHODOLOGY**

The study required that the survey respondent serve a supervisory role (i.e., supervisor, manager, C-suite) in one of the listed nontechnology sectors. Data collection was contracted to Qualtrics. The contract negotiation took about one month and the company delivered the data within two weeks (in June 2020). Targeted data collection was based on the following criteria:

- Employed in the United States
- 18 years of age or older
- Works in a nontechnology sector
- Supervisor or higher position
- Respondent completion time of no less than three minutes

As part of the agreement, the company assigned a project manager to set screeners and quotas for the survey. A soft launch (for 10% of the data) caught survey errors before the full-scale launch. Feedback was obtained from the researcher. The company provided the final data in three days. The project manager excluded individuals who seemed to have completed the survey irresponsibly. The excluded cases stemmed from repeaters (i.e., those who have a duplicate entry for each item), speeders (i.e., those whose completion time is less than three minutes), and randomizers (i.e., haphazard entries

| Path                        | Hypotheses                                                                 |
|-----------------------------|-----------------------------------------------------------------------------|
| **Employee Capability -> Aligned Decision Making** | **H1:** There is a positive association between employee capability and aligned decision making. |
| **Employee Capability -> Intelligence** | **H2:** There is a positive association between employee capability and intelligence. |
| **Employee Capability -> Agility** | **H3:** There is a positive association between employee capability and agility. |
| **IT Flexibility -> Aligned Decision Making** | **H4:** There is a positive association between IT flexibility and aligned decision making. |
| **IT Flexibility -> Intelligence** | **H5:** There is a positive association between IT flexibility and intelligence. |
| **IT Flexibility -> Agility** | **H6:** There is a positive association between IT flexibility and agility. |
| **Aligned Decision Making -> Agility** | **H7:** There is a positive association between aligned decision making and agility. |
| **Intelligence -> Agility** | **H8:** There is a positive association between intelligence and agility. |
like sequentially cycling through the responses). After the researcher provided feedback, the project manager dropped seven additional problematic responses.

Qualtrics software was used to compose the survey (see Appendix for the construct indicators). The valid response count was 136. The mandatory minimum survey time was three minutes. The average was 389 seconds (or 6.48 minutes). Each IP address was distinct, which increased the confidence that the data came from a reasonably random sample. The sample size of 136 respondents was adequate based on power analysis (Hair et al., 2016). The recommended sample size for five independent constructs for detecting 10% R-square at a significance level of p = 0.05 is 122.

Table 3 shows the respondent profile by role and industry. The table exhibits diverse sectors, especially financial services, manufacturing, healthcare, and hospitality. The various roles and industry combinations indicate that the supervisory population was varied and reasonably represented. The most common position count was supervisor (41). This was smaller than the combined counts (66) of middle (22), higher (29), and C-Suite (15) management.

**RESEARCH MODEL RELIABILITY AND VALIDITY**

The first step in validating the research model is ensuring that the measurement model meets the reliability (or composite reliability), convergent validity, and discriminant validity (Hair et al., 2016). The researcher used Smart PLS 3 to evaluate the measurement model and determine the significance levels of the regression coefficients (Ringle et al., 2015). The coefficients for opportunity and risk intelligence were determined by running the PLS model for the model shown in Figure 1 and using the latent values. Figure 2 shows the coefficients between constructs, with the indicators now abbreviated.

Several validity measures evaluate the measurement model. Reliability estimates the intercorrelations of the indicator variables by Cronbach’s alpha or composite reliability. Convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct (Hair et al., 2016). Indicator reliability demonstrates the size of the outer loadings. A significant outer loading could still be weak; therefore, a rule of thumb is that the standardized outer loadings should be 0.708 or higher. Figure 2 shows the outer loadings on the arrows between the constructs and their indicators. All outer loadings were statistically significant at p-value = 0.000,

| Role Name       | Count | Industry Name         | Count |
|-----------------|-------|-----------------------|-------|
| Supervisor      | 41    | Financial Services    | 19    |
| Lower Management| 9     | Healthcare            | 15    |
| Middle Management| 22    | Transportation        | 7     |
| Higher Management| 29    | Consumer Discretionary| 5     |
| C-Suite         | 15    | Manufacturing         | 16    |
| Consultant      | 10    | Education/Research    | 10    |
| Other           | 10    | Consumer Staples      | 4     |
|                 |       | Government            | 9     |
|                 |       | Hospitality           | 15    |
|                 |       | Utility               | 3     |
|                 |       | Real Estate           | 6     |
|                 |       | Other                 | 27    |
which implies \( p < 0.001 \). One outer loading (DM_1, 0.66) is below 0.708; however, it is close enough for retaining because of conceptual justification. Finally, discriminant validity, the extent to which a construct is distinct from other constructs, is illustrated.

**Reliability**

Cronbach’s alpha estimates the reliability based on the observed indicator variables’ intercorrelations (Hair et al., 2016). The desirable value for Cronbach’s alpha should be over 0.70. The study’s constructs showed Cronbach’s alpha ranging from 0.85 to 0.89 (see Table 4). Composite reliability is considered an alternative and better measure of reliability, with the recommended range as 0.8 to 0.9 (Hair et al., 2016). The values ranged from 0.89 to 0.94. They were significant at \( p\)-value = 0.000. Thus, the measurement model established the reliability of the constructs.

**Convergent Validity**

Convergent validity is the extent to which a measure correlates positively with other measures of the same construct (Hair et al., 2016). In assessing convergent validity, the analysis treats a construct’s indicators as alternative approaches for measuring the same construct by calculating loadings. A standard measure to verify the construct level’s convergent validity is the average variance extracted (AVE), which should be above 0.5 (Hair et al., 2016). As shown in Table 4, the AVE for the constructs varied from 0.58 to 0.65. In the case of intelligence (0.89), the AVE is higher because of the correlation
between risk and opportunity intelligence, which are similar constructs. Thus, the measurement model established the convergent validity of the constructs.

**Discriminant Validity**

The logic of discriminant validity is based on the idea that a construct shares more variance with its associated indicators than any other construct (Hair et al., 2016). The researcher ran the model in two steps. The first run used intelligence as a higher-order variable of opportunity and risk intelligence to obtain the respective latent values. The revised model was rerun using the latent values (see Figure 2). The discriminant validity of the analysis is shown in Table 5. The diagonal values show the square root of the average variance extracted, which estimates the correlations within a construct’s indicators. As shown in the table, the Fornell-Larcker analysis established the discriminant validity of the constructs.

**Common Method Bias**

Based on variance inflation values (VIF) and factor analysis tests (Kock, 2015; Podsakoff et al., 2003), the data did not exhibit the common method bias. First, the indicator VIF values vary between 1.6 and 2.6. This implies that the collinearity statistics are within range. VIF values above 3.0 indicate the common method bias (Kock, 2015). Second, PLS-SEM with the factor analysis option shows that five factors emerge with the indicators mapping to their respective constructs. All loadings (except one outer loading) is above 0.7. The analyses rule out the common method bias.

**RESULTS**

Figure 3 shows the significant results obtained from the Smart PLS version 3.3 software (Ringle et al., 2015), while data analysis and procedure are based on a related book (Hair et al., 2016). The significant results determine hypotheses supported at a p-value of 0.05 or less. Table 6 lists each hypothesis, path

**Table 4. Reliability and convergent validity**

|                | Cronbach’s Alpha | Composite Reliability | Convergent Validity (Average Variance) |
|----------------|------------------|-----------------------|----------------------------------------|
| Agility        | 0.89             | 0.91                  | 0.65                                   |
| Aligned Decision Making | 0.85         | 0.89                  | 0.58                                   |
| Intelligence   | 0.87             | 0.94                  | 0.89                                   |
| Employee Capability | 0.88          | 0.91                  | 0.58                                   |
| IT Flexibility | 0.89             | 0.91                  | 0.64                                   |

**Table 5. Discriminant validity**

|                | Agility | Aligned Decision Making | Intelligence | Employee Capability | IT Flexibility |
|----------------|---------|-------------------------|--------------|---------------------|----------------|
| Agility        | 0.81    |                         |              |                     |                |
| Aligned Decision Making | 0.68       | 0.76                    |              |                     |                |
| Intelligence   | 0.65    | 0.64                    | 0.94         |                     |                |
| Employee Capability | 0.47       | 0.61                    | 0.46         | 0.76                |                |
| IT Flexibility | 0.45    | 0.41                    | 0.51         | 0.51                | 0.80           |
coefficient, p-value, and support. Figure 2 focused on the measurement model; it provides the path coefficients and R-square values. The R-square values evaluate the overall structural model, while the coefficients assess the effects of the predictor constructs. The R-square value ranges from 0 to 1, with higher levels indicating more predictive accuracy. The R-square was 0.55 for agility, 0.31 for intelligence, and 0.39 for aligned decision making. The average (1-5 scale) was 4.12 for agility, 3.83 for intelligence, 4.09 for decision making, 4.18 for employee capability, and 3.74 for IT flexibility.

Figure 3 corresponds with Table 6. It provides the significance levels of each path obtained by bootstrapping. The Smart PLS software draws random samples from the data to estimate the path model 5,000 times and determine p values to evaluate the significance level. Bootstrapping determines the standard error. This enables computation of t values and determines the significance level from the p-values. The study regarded a p-value of 0.05 or smaller as statistically significant.

Figure 3 and Table 6 indicate that five hypotheses are significant and three are insignificant. In Figure 3, the thickness of a line reflects the coefficient’s strength. The figure shows that employee capability (p = 0.98) and IT flexibility (p = 0.14) do not directly affect agility. However, employee capability, which strongly affects aligned decision making, has a weaker and significant impact on intelligence. IT flexibility substantially impacts intelligence (coefficient 0.38); however, it does not affect aligned decision making.

Aligned decision making and intelligence are the most proximate to agility. The two serve as mediating variables for employee capability and IT flexibility. Aligned decision making has a strong effect (coefficient = 0.437, p = 0.000) on agility. Intelligence has less but robust effect (coefficient =
0.311, \( p = 0.000 \)). Employee capability affects both aligned decision making and intelligence, which affect agility. IT flexibility significantly affects intelligence, which affects agility. Thus, both aligned decision making and intelligence serve as mediating variables.

Additional analysis can provide an alternative perspective. Although the direct effects of employee capability and IT flexibility on agility are insignificant, the indirect effects are meaningful. The total indirect effect of employee capability is substantial, with a t-statistic of 5.15 and a p-value of 0.000. Similarly, IT flexibility’s total indirect impact is significant, with a t-statistic of 3.00 and a p-value of 0.003. The comparison indicates that employee capability has a more substantial influence than IT flexibility.

**DISCUSSION**

**Implications for Theory**

This research extends the study by Chen and Siau (2020), which found significant effects of (BI&A) and information infrastructure flexibility on organizational agility. They recommended that BI&A is a critical component of an organization’s agility, as well as emphasized a similar role for infrastructure flexibility. They suggested that future research evaluate additional factors to improve the explained variance. Specifically, they advised that IT personal competency can improve BI&A, helping to improve decisions regarding responses to opportunities and threats. The current study added employee capability and decision making to the three constructs examined by Chen and Siau (2020).

The study aimed to determine the strength of antecedents’ effects on organizational agility in the nontechnological sectors. The uncertainty reduction theory and three streams of agility literature (e.g., dynamic capabilities, decision making, and BI&A competitive advantage maturity model) were employed to propose a research model. The research model included intelligence, aligned decision making, employee capability, and IT flexibility. Thirty-nine indicators were used. Intelligence, a higher-order construct, was composed of opportunity and risk intelligence. Data analysis revealed that the research model predicted 55% of the organizational agility variance, indicating a moderate-to-strong prediction as found in several information systems models like the technology acceptance model (TAM, Riemenschneider et al., 2002). Aligned decision making and intelligence had direct and mediating effects on agility. Employee capability and IT flexibility did not directly affect agility, but both variables had substantial indirect effects. Consequently, the two variables enhanced the research model’s predictive power. A supervisor can rate the study’s 39 indicators to obtain a workable agility index, weighted if desired.
The research found that each construct has significant predictive power. Aligned decision making and intelligence directly predict agility. Although employee capability does not directly affect agility, it has strong indirect effects through aligned decision making and intelligence. IT flexibility is vital even in nontechnological sectors as IT finds a new role in morphing products into products integrated with services. For example, cars, gyms, homes, and appliances are slowly transforming into electronic products and services. One could expect an organization’s definition to gradually shift to a portfolio of risk and opportunities supported by the intelligence. Future research could offer a framework that complements human intelligence and AI with decision-making capabilities. Currently, the human component seems more impactful than the technology component.

Future research can improve measurements by treating the first-order constructs in this study as higher-order constructs. For example, the study treated intelligence as a higher-order construct. One could consider treating employee capability as a higher-order construct composed of core competency and adaptability. One may also separate the structural and process aspects of IT flexibility. Similarly, one can split aligned decision making into lower-order constructs. It is possible to collect data from both technology and nontechnology sectors for post-hoc comparisons.

**Implications for Practitioners**

Currently, the nonIT sectors are adopting digitalization (using IT to enhance business processes and operations) and digital transformation (rethinking the entire business model, Kamal, 2020; Siau, Woo, et al., 2022). In an uncertain environment, both adoptions necessitate agility. Intelligence and aligned decision-making factors are critical in enhancing agility during uncertainty. Intelligence techniques are popular among the practitioner community. Most university IS programs offer an analytics major to fill the demand (Lyytinen et al., 2021). Business intelligence vendors provide useful intelligence software. Business majors other than information systems also offer analytics coursework. One can reasonably expect that most organizations in the nontechnology sectors have developed some degree of risk and opportunity detection capability.

Once a risk or opportunity is detected, decision makers may face numerous alternatives. Due to the uncertainty fog and limited response time, decision makers may rule out optimization (Kahneman & Lovallo, 1993; Samuelson & Zeckhauser, 1988). The guiding compass will likely emerge from the organization’s values, mission, and strategy. The mission may need to be flexible so that a company can pivot during uncertain times. For example, if a home builder’s mission is defined in brick-and-mortar terms, it is less flexible than one expressed around the experience of homeowners. Decision makers need heuristics for choosing among alternatives (Kahneman & Lovallo, 1993). For example, they may select high-risk options, preferred if the uncertainty is more likely to result in opportunities, or low-risk options, desirable if the business environment is relatively stable. Market surveillance and aligned decision making can help calibrate the risk.

During uncertain times, transparency can improve decision-making efficiency and effectiveness by disseminating data and actions to employees and other stakeholders so they can debate and make appropriate choices. Transparency builds trust between superiors and subordinates, which is essential for rapidly implementing decisions. Due to response time pressures, people will make mistakes. Trust is engendered when errors are evaluated considering situational demands. Mistakes should preferably lead to learning, not finger-pointing.

Employee capability and IT flexibility factors are vital; however, both work through intelligence and aligned decision making. Seven items measure employee capability in the facets: (1) job skill; (2) interpersonal skills; (3) motivation; (4) coordination ability; (5) adaptability; (6) creativity; and (7) resilience. A single employee might not have all the seven attributes, but a department or a division should aim for an appropriate mix. Softer skills like creativity and resilience may become critical during uncertain times. For instance, when a disaster strikes, the creative employee will search for novel ways of serving customers. The resilient employee will focus on solutions instead of obsessing on problems.
There is a natural bias to focus on the primary workplace in attaining IT flexibility. Pandemics can result in lockdowns and work-from-home arrangements. Employers may regard “home” as “less office” or separate because of geographical distance and a historical mindset that views home for leisure and rest. Thus, the office may have powerful computers attached to dual monitors and high-speed Internet connectivity. In contrast, there may be no plan for a productive work environment from home, which may vary according to the employees’ purchasing power. Even if companies can fix distant hardware and connectivity issues, the employees may not have practiced efficient process routines from remote sites. Disaster planning and contingency routines may mitigate such challenges. Moreover, revised work norms entail more emphasis on IT flexibility arrangements.

Limitations
Research data was collected in June 2020, at the height of the pandemic. Although there was strong anecdotal evidence from business media that nontechnology companies were becoming more agile, the timing might have been a bit early. In retrospect, the concern is somewhat mitigated because companies did modify their business practices. For example, due to employee preferences, many companies adopted a hybrid model for remote office work (two or three days per week) even as COVID-19 cases fell. Companies are also adapting to supply chain shortages.

Still, there is ambiguity regarding the long-term rate of change. The scope of research did not include whether the more agile companies showed more improvement than their nonagile counterparts in terms of the various success measures (Siau et al., 2010). Thus, the link between agility and success is missing.

Data was collected from a large set of organizations. The approach increased the diversity of the company sectors and reduced the company-specific oddities that might arise from using a few organizations. A supervisor/manager/C-suite respondent was employed to answer questions for the organization. On one hand, the method is plausible because an organization is not a person (and the study needs to use a proxy). Still, such a respondent may have difficulty estimating representative answers for the organization and is, therefore, likely to be affected by familiarity (for example, to a department or division level). During the initial onset of COVID-19, managers and supervisors (as in the case of the author’s university) held frequent Webinars and online meetings to keep employees abreast of decisions and actions. One would hope that the study’s respondents were aware of issues at the organizational level.

The research also has minor limitations. A reputed data collection vendor can open the door to many companies. Still, because it serves as an intermediary, the respondents may not feel as connected with the researcher to provide the best data. There is also the risk of demand effects as respondents portray their organization better despite the anonymous nature of the survey.

Contributions of the Study
The study makes several significant contributions. First, the study blends dynamic capabilities, decision making, and a BI&A competitive advantage maturity model to identify the critical antecedents of agility in nontechnological sectors. Second, the research identifies intelligence and aligned decision making as essential in determining agility. Third, the study finds that employee capability and IT flexibility affect agility through intelligence and aligned decision making. This, in turn, serves as mediating variables. Employee capability and IT flexibility do not affect agility directly. Fourth, the 39-indicator scale of the antecedents can serve as a preliminary agility index. Future research should enhance the questionnaire by identifying components of the first-order constructs and replacing them with higher-order constructs.

CONCLUSION
Substantial disturbances caused by hurricanes, earthquakes, fires, and severe electric power require an agile response, even in relatively stable sectors like teaching and hospitality (Dohaney et al., 2020).
Although global disruptions like COVID-19 may be rare, they can cause significant disruptions (Gössling et al., 2020; Sakurai & Chughtai, 2020). Emerging technologies like AI and data science will significantly affect nonIT sectors (Berente et al., 2021; Kelleher & Tierney, 2018; Sejnowski, 2018; Wang & Siau, 2019).

In parallel, digitalization is rising in the nonIT sectors (Kamal, 2020), resulting in digital transformation (Majchrzak et al., 2016). The digital transformation and intelligence delivery will be characterized by a postmethodology systems development era marked by dynamism, flexibility, and adaptability (Siau, Woo, et al., 2022). In this current era, software design and development speed is driven by surging demand for digital capabilities, focusing on strategy, value creation, people relationships, and societal impacts (Siau, Woo, et al., 2022). Future research can examine the link between organizational agility and the newer systems development approaches like agile and DevOps, which emphasize speed of delivery and integration (Beard et al., 2022).

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CONFLICT OF INTEREST

The author of this publication declares there is no conflict of interest.
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APPENDIX

Constructs Questionnaire: Determinants of Agility in Companies in the NONIT Sectors

The questionnaire provides separate entries for roles and industry. Latent constructs are measured using the following Likert scale: strongly disagree (1); somewhat disagree (2); neither agree nor disagree (3); somewhat agree (4); and strongly agree (5).

Agility
My organization displays ability in the business environment for:

1. Detecting risks
2. Detecting opportunities
3. Assessing risks
4. Assessing opportunities
5. Responding to risks
6. Responding to opportunities

(Intelligence is a higher-order construct composed of risk and opportunity) Intelligence

Risk Intelligence
My organization continually scans the environment to assess RISK:

1. During uncertainty
2. During relative stability
3. Arising from the financial area
4. Arising from the political area
5. Arising from the biosphere area (e.g., a pandemic like COVID-19)
6. Arising from the technological area
7. Arising from the regulatory area

Opportunity Intelligence
My organization continually scans the environment to assess OPPORTUNITY:

1. During uncertainty
2. During relative stability
3. Arising from the financial area
4. Arising from the political area
5. Arising from the biosphere area (e.g., a pandemic like COVID-19)
6. Arising from the technological area
7. Arising from the regulatory area

Aligned Decision Making
In my organization, DECISION MAKING is characterized by:

1. Alignment between strategy, mission, and values
2. Alignment between management and other employees
3. Transparency
4. Tolerance for unforeseen mistakes
5. Trust between superiors and subordinates
6. Learning, regardless of positive or negative outcomes

Employee Capability
In my organization, EMPLOYEES are:

1. Proficient in job skills
2. Proficient in interpersonal skills
3. Motivated
4. Skilled in coordinating
5. Adaptive to the changing environment
6. Coming up with creative solutions
7. Resilient in adverse circumstances

IT Flexibility
The IT facilities facilitate:

1. Rapid switching from face-to-face to remote work
2. Quality IT hardware resources at the primary workplace
3. Quality IT hardware resources at remote workplaces
4. Quality connectivity from remote workplaces
5. Processes for smooth workflow from the primary workplace
6. Processes for a seamless workflow from remote workplaces