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Unravelling the Origins of Infobesity: The Impact of Frequency on Intensity

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Abstract

Infobesity is characterized by information overload whereby firms and decision makers collect more information than they need, or they can efficiently use. While recent studies have begun to unravel the antecedents of infobesity in organizations, there is a need to examine the relationship between the frequency and the degree of experiencing infobesity originating from enterprise systems. We use a research design that integrates inductive analytics and abductive discovery to uncover the interaction of multi-level antecedents of infobesity and conclude that the rate at which firms encounter infobesity drives the perception of the intensity at which the overload will be experienced.

1. Introduction

Infobesity is a condition characterized by information overload whereby firms and decision makers collect more information than they need or more information than they can efficiently use. Infobesity can limit firms' workers' attention capacity thereby making it increasingly difficult to effectively use all available information [1, 2]. Organizations in a variety of industries face infobesity and try to find means to cope with it to identify the most important data in a timely manner. For many firms, infobesity has become a blind spot as they have become desensitized to being overwhelmed with information. Moreover, the abundance of information that is of inferior quality implies infobesity is a societal issue. As firms' information environment continues to get dominated with technological investments and advances, the challenge of infobesity is not diminishing anytime soon. This puts firms and its decision makers at a greater risk of infobesity which can compromise their performance outcomes [3].

Recent studies have begun to explain how firms perform in the presence of information overload [4]. However, there remains a gap in comprehensively understanding the interplay of factors residing across multiple levels of analyses which can address infobesity. There remains a need to carefully examine antecedents of infobesity so that decision makers can be equipped with the capabilities to transform excess information and make it value-adding. Infobesity in firms is caused by an abundance of information which differs in its intensity and frequency.

We maintain that the phenomenon of infobesity can be characterised by several dimensions. This study aims to study the relationship between two such dimensions, namely, degree or intensity of infobesity, and frequency of infobesity. While the degree of infobesity deals with *how much* information creates overload in the organizations, the frequency of infobesity deals with *how often* the organizations have to deal with overwhelming amounts of information.

Practical exemplifications of how frequency and degree of intensity affect firms can be found in instances of two types of firms. On the one hand, an e-commerce firm during the many holidays throughout the year will have to deal with a drastic increase in customer traffic on their websites. This can create a high frequency of infobesity as it occurs multiple times of the year. On the other hand, a typical publicly traded firm that has to report its financial results every quarter will encounter infobesity rarely. Since this event happens every quarter, it is possible the firm has developed automated processes to conduct it and hence is not overwhelming for the firm.

Recent studies have begun to explore the impact of frequent interactions on consumers' cognitive load [5, 6]. For instance, while the online news disseminated during the COVID-19 pandemic was

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critical to inform people about the disease, the overwhelmingly high frequency of such news also led to infobesity [7]. Such high frequency of news creates cognitive burden not only for individuals, but also for organizations. Organizations have to manage the high frequency of incoming information to take timely decisions in order to continue doing business. This study is a step towards unravelling the origins of infobesity, specifically its frequency and degree, in order for organizations to respond to crises like the pandemic. Hence, there remains a need to understand how different frequencies of infobesity from enterprise systems can create different degrees of infobesity at the organization-level.

Hence, we aim to open the black box of infobesity by comprehensively explaining the interplay of different levels of predictors, specifically frequency of infobesity, that influence the firm's infobesity experience. Doing so can provide researchers and managers with a magnified view into the firms' information environment and effectively manage with it. The firm's performance outcomes such as its innovation capabilities are largely influenced by the timely access to quality information. Furthermore, such a study is a step towards identifying how different mechanisms can be used to effectively cope with specific dimensions of infobesity. Moreover, we explore whether seasonal bursts of information overload can have a similar impact on the intensity of infobesity as a constant barrage of information. We aim to bridge this gap by leveraging a research design that has gained credence in recent Information Systems scholarship [8-10]. This research methodology integrates induction-based data-driven analytics approaches with abduction to uncover emergent patterns from the data. Hence, this study focuses on the following research question:

RQ: How does the frequency of encountering infobesity impact the degree with which it is experienced in organizations?

We use a sequence of induction followed by abductive reasoning as our methodological approach. Decision tree induction serves as the basis for identifying tacit patterns in the data, which serves as an input to the abductive discovery process which involves understanding these patterns to develop the best plausible explanations. Decision tree induction allows us to reveal key pathways of predictors at different levels of analyses that elucidate the combination of different predictors that create infobesity in the firm. Through abduction, we can summarize our key theoretical findings to offer the best possible explanations and complete the knowledge creation cycle.

We analyse a unique survey dataset collected from Chief Executive Officers, Chief Financial Officers, Chief Information Officers, Chief Marketing Officers and other senior decision makers from a sample of more than two hundred U.S. firms about their information overload and innovation activity. Data was collected on the degree of information overload experienced by the firms, sourced from information systems including Supply Chain Management, Customer Relationship Management, and Enterprise Resource Planning systems. Furthermore, extensive data on collaboration efforts with partners was also collected.

We find that when rarely encountering any infobesity, firms are likely to perceive their acquired information to be the right amount and not a source of overload. On the other hand, when decision makers are constantly burdened by an abundance of information, the intensity of infobesity will be extremely high. Moreover, moderate frequencies of infobesity yield moderate or high degrees of infobesity based on multiple levels such as firm-level and industry-level. These findings have implications for the attention-based view of the firm [11], and explore the forces controlling decision makers' limited attention.

The rest of this manuscript is organized as follows. In the next section, we present an overview of related literature. Subsequently, we describe the data used in the empirical investigation and the key information attributes (i.e., factors that associated with firm infobesity outcomes) essential to our theory development. We then elaborate on the tree induction methodology. In the next section, we present findings from the sequence of decision tree induction and abduction. We conclude by discussing the implications of our findings and offering rich managerial implications of our research.

2. Literature Review

2.1. Increasing complexity in the firm's information environment

Organizations are information processing systems and where the imbalance between the firms' information processing capabilities and the information load encountered can create information overload or underload [12]. As firms' information environment becomes increasingly complex and abundant with excess data, they are being exposed to the detrimental phenomenon of Information Overload or Infobesity. The increasing use of different types of information systems - such as enterprise systems, email systems – has been associated with infobesity [4, 13]. Prior studies have researched the antecedents and consequences of infobesity [1, 2, 14]. Managers often seek information to indicate a commitment to rationalism, to appear dominant among competitors which they believe might improve their decision making [15]. The increasing use of information technology has exacerbated the problem of infobesity as firms are being exposed to overwhelming amounts of information than ever before. Infobesity can create stress and frustration among individuals as they are constantly interrupted by a torrent of information [1]. Large degrees and frequencies of information can have detrimental effects on organizations' success. By affecting workers' ability to take decisions and solve problems timely, infobesity can reduce productivity, hinder learning, and ultimately affect the firms' performance and profits [1, 3]. Firms can lose productive time as their workers have to deal with overwhelming amounts of information with low value [1].

The firm's information environment is influenced by various sources which exist at different levels on analyses including the firm-level, technology use level, partner-level, and industry level.

Firstly, firm-level predictors including investment in Research and Development and Information Technology determine its resource endowments and consequently its digitally enabled activities and access to sources of information [16-19]. Furthermore, the firm's market scope and merger and acquisition strategy influence the amount and diversity of information a firm is exposed to [20].

Secondly, a firm's technology use and digital resource endowments influences the quantity and quality of the firm's information environment [21, 22]. Prior research has established that IT-enabled capabilities related to information management and processing have a positive impact on the organizations' performance such as productivity enhancement, profitability improvement, cost reduction, etc. [23-28]. By implementing enterprise systems such as Enterprise Resource Planning, Customer Relationship Management and Supply Chain Management systems, firms and decision makers are able to expand their knowledge sources by acquiring vital information from their value chain, and can thereby improve their innovation outcomes [29-31]. However, the use of these technologies also exposes the firm to an abundance of information. Note that though firms utilize a variety of enterprise systems to meet their business and information processing needs, Enterprise Resource Planning systems, by definition, encapsulate all of these systems (such as Human Resource Management Systems, manufacturing systems, and financial systems). Customer Relationship Management and Supply Chain Management systems are not always part of Enterprise Resource Planning systems; furthermore, due to their boundary spanning roles, they are key sources of knowledge.

Thirdly, the unequal distribution of knowledge within the organization and its environment incentivizes the firm to participate in collaborative activities to access additional knowledge [32], which creates another source of information existing at the partner-level. Firms can establish multiple partnerships with suppliers and customers in its value chain network to access a larger variety of information [33]. By gaining new and diverse knowledge from its partners, the firm is more likely to face an excess load of information. Moreover, existing literature has identified the benefits of employing collaboration technologies within teams [34, 35]. This creates an additional source of information which can lead to infobesity.

Lastly, the culmination of advances in information and communications technology (ICT) has led to wide- spread automation and digitalization at the industry-level. With increased technical capital, industries' decision-making speed has increased, along with quicker production of high-quality products and services. This has led to industries becoming fast-paced and dynamic witnessing a fast pace of innovation or high clockspeed [36].

2.1. Frequency and degree of infobesity

Prior literature has recognized infobesity in organizations is affected by characteristics of the information such as its quantity, intensity, frequency, and complexity [2, 37]. Infobesity in organizations can create technostress and affects the attention retention capacity of individuals [38] which leads to further negative reactions such as frustration and dissatisfaction [1, 39]. This can hinder individuals' productivity and performance which can have detrimental consequences on their decision-making and innovation activities [3, 12]. Past studies have begun to unravel the impact of information overload on consumers as a result of frequent dispersal of information through social media platforms and online advertising [6, 40]. Furthermore, past research includes examination of the impact of frequency of interruptions in organizations on workers' performances [5].

However, there remains a need to carefully examine antecedents of different degrees of infobesity so that firms and its decision makers can be equipped with the capabilities to transform excess information and make it value-adding. This study explores how different frequencies of information from enterprise systems creates different degrees of infobesity.

We study the relationship between two dimensions of infobesity; frequency and degree of infobesity. While the degree of infobesity deals with *how much* information creates overload in the organizations, the frequency of infobesity deals with *how often* the organizations have to deal with overwhelming amounts of information. The degree of infobesity measures the different levels by which information is a source of overload, and when firms and decision makers collect more information than they need and more information than they can efficiently use. On the other hand, the frequency of infobesity measures the frequency of instances of infobesity, or how often organizations are likely to encounter infobesity. These two dimensions are systematically differentiated as elaborated in the Measures section (3.2).

By doing so we explore whether seasonal bursts of information overload can have a similar impact on the intensity of infobesity as a constant barrage of information. We aim to open the black box of overload by comprehensively explaining the complex interplay of multiple levels of predictors, specifically frequency of infobesity, that influence the firm's infobesity experience. Specifically, we take a step towards understanding the interdependency between two characteristics of infobesity.

3. Methods

3.1. Data

This study uses survey data collected from a sample of 249 U.S. firms [4]. Data collection was facilitated by a reputed market research firm. The survey respondents include presidents, vice presidents (VPs), chief executive officers (CEOs), chief financial officers (CFOs), chief information officers (CIOs), and other senior decision makers of the firms in the sample. The sample was drawn from a mix of eight high and low clockspeed [36] industries — computer hardware & services, electronics & telecommunications, food & beverages, chemicals & pharmaceuticals, transport & logistics, retail, business services, and energy & mining. The distribution of firms' size, age and revenues is representative of the population of US firms. Data was collected on the degree and frequency of infobesity experienced by the firms, stemming from the use of from information systems including Supply Chain Management, Customer Relationship Management, and Enterprise Resource Planning systems. Furthermore, extensive data on collaboration efforts with business partners across the value chain, and innovation outcomes was also collected. Each respondent also provided data about their firm's business activities such as new product development, IT and R&D expenditures, and M&A activity.

3.2. Measures

3.2.1. Key outcome – degree of infobesity. We are interested in inductively building theory to explain the *Degree of Infobesity* faced by firms. We collected data about the degree of infobesity faced by firms and its decision makers using SCM, CRM and ERP systems individually on a 7-point scale. The degree of infobesity was measured as a combination of three factors including: if the information collected via these systems was more than needed; if the information collected via these systems was more than could be efficiently used; if the information collected via these three different systems was a source of information overload. Then, for each firm we took the sum of the three information systems and classified firms as belonging to one of High, Medium, or Low degree of Infobesity. Firms with values in the top one-third ranges were classified as facing a high degree of Infobesity. Firms with values in the bottom one-third ranges were classified as experiencing a low degree of Infobesity. The remaining middle value firms were classified as facing a medium degree of Infobesity. Next, we describe the information attributes we provided to induce trees and build our theory.

3.2.2. Frequency of infobesity. We collected data about the *Frequency of Infobesity* faced by firms and its decision makers using SCM, CRM and ERP systems. Frequency of infobesity is measured by how often firms experience infobesity on a scale ranging from 1-7 (Never, Very Rarely, Rarely, Occasionally, Frequently, Very Frequently, Always) from each of the three enterprise systems. For each firm we took the sum of the frequencies of infobesity from the three information systems and classified firms as belonging to one of High, Medium, or Low frequency of infobesity. Firms with values in the top one-third ranges (Frequently, Very frequently, and Always) were classified as facing a high frequency of infobesity. Firms with values in the bottom one-third ranges (Never, Very rarely) were classified as experiencing a low frequency of infobesity. The remaining middle value firms (Rarely, Occasionally) were classified as facing medium frequency of infobesity.

3.2.3. Firm-level attributes. We laid out 4 firm-level information attributes to understand Infobesity. These were *IT Investment*, *R&D Investment*, *M&A Activity*, and *Market Scope* namely.

A firm was classified as having High IT Investment if average spending on IT hardware, software, and services as a percentage of total sales was greater than 16%. On the other hand, firms with average IT spending less than 6% of total sales were classified as having Low *IT Investment*. The remaining firms with 6% – 16% average IT spending were classified as having Medium *IT Investment*. These values were chosen to divide the data equitably in three partitions based on the distribution of the data points.

Similarly, firm's *R&D Investment* was categorized as High/Medium/Low based on average spending on research and development as a percentage of total sales. A value greater than 16% was classified as High, less than 6% was classified as Low, and remaining values ranging from 6% - 16% were classified as Medium.

The third firm-level information attribute we captured is *M&A Activity.* Firms with more than 5 mergers and acquisitions were classified as exhibiting High *M&A activity*. On the other hand, firms that undertook less than 3 M&As were classified in the Low category. The remaining firms which had 3 or 4 mergers and acquisitions were categorized as demonstrating Low *M&A Activity.*

Firms were classified as having one of three *Market Scopes* namely International, Regional or Domestic.

3.2.4. Technology-use attributes. Our study explores the use of information systems at three levels namely: Inter-firm, Intra-firm, and Market-facing technology use. *Inter-firm* technology use was measured through the utilization of ERP systems. We collected information on the *ERP system use* by firms to manage their internal information. Firms that did not employ any ERP systems were classified as possessing *No ERP Use,* whereas firms that employed ERP systems were classified in the *ERP Use* category.

Intra-firm technology use was measured through *SCM system use* and *Market-facing* technology use was measured through *CRM system use*. For SCM and CRM systems, we collected data on the proportion of customers and proportion of suppliers connected to the systems respectively. Hence, a firm with *High SCM Use* is one where greater than 80% of its suppliers are connected to the SCM system. Similarly, a firm *High CRM Use* is one where greater than 80% of its customers are connected to the CRM system. On the other hand, firms with less than 20% of its suppliers and customers on their SCM and CRM systems, were classified as having *Low SCM Use* and *Low CRM Use* respectively. The remaining middle firms with 20% - 80% of its suppliers and customers connected to a given firm's SCM and CRM systems, were categorized in the *Medium SCM Use* and *Medium CRM Use* category respectively.

3.2.5. Partner-level attributes. We captured firms' *Upstream* and *Downstream* partner network through the *Number of Suppliers* and *Number of Customers* respectively. Number of customers and Number of Suppliers were coded into high, medium, and low values based on top, middle, and lower one-third categories of values.

3.2.6. Industry-level attributes. We classified a firm in a High *Clockspeed* industry if its average product lifecycle was less than 1 year. A value of Medium was assigned if the average product lifecycle is greater than one year, but less than 2 years. If the average product lifecycle is more than 2 years, it is classified as belonging to a Low *Clockspeed* industry.

3.3. Methodology

Our methodology to build theory consists of induction followed by abduction. We employ decision tree induction, a supervised machine learning methodology which reveals complex underlying relationships in the data that otherwise are tacit and left unidentified. The induction algorithm utilizes the most informative attributes that influence the outcome to provide context-specific rules [9, 41]. After identifying patterns in the data, we make sense of the patterns by conducting abductive reasoning to develop the best possible generalized explanations. This iterative process integrates induction and abduction to test various choices, improves predictive performance, and ultimately completes the knowledge production cycle to develop theory.

Prior to inducing trees, a key process to undertake is that of data partitioning. Data partitioning involves repeatedly drawing two random, mutually exclusive training and testing subsamples of observations from the data. The knowledge from the training partition is used to identify tacit connections and grow the decision trees. Then, the disjoint set of observations in the testing set are used to test the predictive accuracy of the decision rationale discovered in the training set.

After partitioning the data, the decision tree induction methodology involves two main steps: inducing the trees, followed by pruning the trees. Firstly, the C4.5 algorithm is used for inducing the trees on the training partition. We make use of the open source Weka data mining tool for data partitioning, inducing trees, and pruning trees. Secondly, the induced trees are pruned using the testing partition which increases the robustness of the knowledge discovered from the trees. There are two key inputs for decision tree induction: (1) firms described by all information attributes and (2) infobesity experienced by firms. After employing the C4.5 induction algorithm, the output is a decision tree that unveils tacit relationships of attributes leading to similar final outcomes. The C4.5 algorithm utilizes the concepts of information entropy and information gain ratio to reduce impurity in determining which attributes lead to terminal nodes or leaves. Hence, the tree induction methodology iteratively groups together firm-level observations that not only demonstrate similar information attributes, but also lead to the common final outcome. This hereby leads to the output decision trees retaining only the most informative attributes.

The second stage of our research methodology is abductive reasoning which involves the explanation of the rules discovered in the induction process. The abduction process requires the researchers' expertise and judgement to offer the most plausible explanations, and not confirmative logic, for the observations (derived from induction) [42]. The process of abductive reasoning is fundamentally different from deductive reasoning in that deduction stems from the guaranteed presence of given evidence. Hence, conclusions drawn from deductive reasoning are necessarily true as they were based on facts that were true [42]. On the other hand, abduction requires judgement to arrive at inferences that are the best possible explanation of the evidence available.

The process of abductive reasoning is exemplified during medical diagnosis. When a patient demonstrates a combination of symptoms, physicians employ abductive reasoning to arrive at a prognosis that has the highest probability of explaining the given symptoms. Hence, from the context-specific rules induced from the decision trees, we employed abductive reasoning to propose generic explanations. By offering plausible explanations of the rules discovered by inducing trees, the process of abduction completes the knowledge creation cycle.

4. Findings from Induction

In order to maintain robustness, we rely on the three heuristics of (1) high prediction accuracy, (2) high parsimony, (3) high reliability and select the best representative tree which is synthesized and presented in Figure 1. The most informative attribute is the topmost attribute in the best representative tree. Importance of attributes decreases as we move away from the top of the tree towards its leaves. The best representative tree chose Frequency of Infobesity as the top-most and most informative attribute. SCM System Use was the second most important attribute for explaining infobesity. On the other hand, other inputs including firm-level, partner-level and industry-level attributes were either not included in the tree or were at lower levels. These findings aid in answering our research question and lend credence to our core premise that the frequency of infobesity has substantive influence on the degree of infobesity experienced by firms and its decision makers. Figure 1 summarizes the induced results and presents how firms experience different degrees of infobesity as a consequence of different frequencies of infobesity.

Impact of Frequency on Degree of Infobesity

Frequency of Infobesity = Low
| SCM System Use = Low: Low DOI
| SCM System Use = Medium + High: Medium DOI
Frequency of Infobesity = Medium
| SCM System Use = Low: Low DOI
| SCM System Use = Medium
| | Clockspeed = Low
| | | IT Investment = Low + Medium: Medium DOI
| | | IT Investment = High: High DOI
| | Clockspeed = Medium + High: Medium DOI
| SCM System Use = High: High DOI
Frequency of Infobesity = High: High DOI

Note: DOI = Degree of Infobesity

Figure 1. Degree of Infobesity

It is essential to clarify that the trees induced are not reflective of the exact rules used by decision makers in firms, but instead are robust approximations of the tacit underlying decision rationale. The patterns in the data revealed from inducing trees allows us to extract three main rules as presented next.

Rule 1: Low frequency doesn't create high infobesity

The decision tree revealed that firms' decision makers never or very rarely experiencing infobesity are likely to never face a high degree of infobesity. Hence, firms experiencing a low frequency of infobesity are likely to experience a low or medium degree of infobesity depending on their level of employing intra-firm technology systems. We found more than nine percent of firms in our sample facing a low degree of infobesity as an outcome of a low frequency of infobesity and employing only a low-level use of SCM systems. On the other hand, more than ten percent of firms were found to experience a medium degree of infobesity if they face a low frequency of infobesity but a higher-level deployment of SCM systems within their organization.

Rule 2: Medium frequency creates moderate to high degrees of infobesity

When a firm rarely or occasionally experiences overload, it is likely to experience moderate to high degrees of infobesity. Almost fifty percent of the firms in the sample when facing a medium frequency of infobesity, expected the amount of information to be more than needed and more than what could be efficiently used. Under a medium frequency of infobesity, a high or medium degree of infobesity is determined by factors at the technology-use, industry, and firm level. If the firm employs a minimal use of SCM systems, it is likely to experience only a medium degree of infobesity. On the other hand, having a high proportion of its suppliers connected through SCM systems, exposes the firm to a high degree of infobesity in the presence of medium frequency of infobesity.

The tree revealed industry clockspeed to be an important attribute for determining firms' decision makers' degree of experiencing infobesity when facing a moderate frequency of infobesity and medium SCM system use. In particular, belonging to an industry with long product lifecycles, exposes firms to moderate degrees of information overload. On the other hand, firms in industries with shorter lifecycles can experience high degrees of infobesity when the firm has a high spending on IT hardware, software, and services.

Rule 3: High frequency creates a high degree of infobesity

We discovered that when firms' decision makers always or very frequently face information overload, they are more likely to experience high degrees of infobesity. The decision tree revealed more than forty-five percent of firms in our sample that encountered high degrees of infobesity as a consequence of experiencing information overload at extremely high frequencies. This implies that when facing infobesity very often, firms' sources of information cannot be of low or moderate degrees of infobesity. These findings lead to the conclusion that frequency of infobesity is an important determinant of degrees of infobesity.

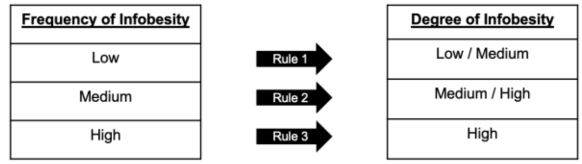

Figure 2. Induced results

5. Discussion

Through our induction process, we identified context-specific rules which explained the combination of different predictors causing infobesity [10, 43, 44]. After inducing these three rules from the decision trees, we perform abductive reasoning to offer the best plausible explanation of the patterns revealed. Doing so will extend the knowledge cycle by allowing us to identify different explanations, and ultimately arrive on the most plausible explanation for the discovered (induced) findings.

5.1. Insights from abduction

From all the three rules induced, we can conclude that the frequency at which firms' decision makers experience infobesity is a deterministic antecedent to explain the degree at which the firm will experience the infobesity.

From Rule 1, we found that when rarely encountering any information overload throughout their lifecycles, firms are likely to perceive their acquired information to be the right amount and not a source of overload.

On the other hand, from Rule 3, we found that when decision makers are constantly burdened by an abundance of information, the intensity of infobesity will be extremely high.

Rule 2 revealed moderate frequencies of infobesity yield moderate or high degrees of infobesity based on the levels at which the firm implements enterprise systems, its product lifecycle and its IT expenditures. Hence, the rate at which firms encounter infobesity drives the perception of the intensity at which the overload will be experienced.

Through the abduction process above, we are able to offer plausible explanations for understanding the relationship between frequency and degree of infobesity in the firm. With the advent of IT, if firms can manage the frequency with which they are likely to experience infobesity, they can take a step towards managing the intensity of infobesity. For instance, if firms can predict when they are likely to high frequency of information, they would be better prepared to handle its intensity.

While studying overload is necessary, we recognize that it is not sufficient. To complete the knowledge production cycle, we have further examined the impact of infobesity on the firms' innovation outcome which allows us to understand the consequences of infobesity on the firm's performance. Our findings establish infobesity as an important predictor of innovation. We discovered that coping with moderate levels of infobesity requires digital collaboration and an extensive supplier network. By digitally collaborating with their suppliers and customers, decision makers can make effective use of their abundant knowledge by filtering information about market needs they can develop new products and services that demonstrate enhanced features [4, 45]. These findings are beyond the scope of this research, but indirectly examine the impact of frequency and degree of infobesity on the firm's innovation outcome.

5.2. Contributions

Past literature has identified frequency and degree of infobesity to be separate causes of infobesity, however this study reveals the nuanced and interdependent relationship of degree of infobesity on frequency of infobesity. Moreover, this study offers an extremely valuable contribution to the literature on information overload. We move IS scholarship forward by building on the theoretical construct of infobesity which captures the problem of abundance in organizations caused by the multiplying addition of new technologies. The attention-based view of the firm recognizes that decision makers actions depend on their attention which is a scarce resource [11]. With the firm's information environment becoming exponentially complex, infobesity further clouds decision makers' attention. This study opens the black box of infobesity by comprehensively explaining the complex interplay of multiple levels of predictors, specifically frequency of infobesity, that influence the firm's infobesity experience.

5.3. Limitations

Our study suffers from certain limitations. First, while we studied infobesity derived from enterprise level information systems, we did not consider social media platforms as a source of information overload. We recognize the growing importance of digitized social networks such as Instagram and Twitter, and the overwhelming amount of information they generate for organizations which can fundamentally alter the frequency with which decision makers experience infobesity [46]. However, we remain hopeful that our findings will remain applicable to these technologies and consider them as an additional possibility for acquiring deeper insights to study infobesity in organizations.

Second, our data was collected from one CXO for each firm and hence is applicable at the organization level. This could imply that our work suffers from a degree of generalizability in the context of distinct operations of independent teams. However, we believe this limitation paves the way for future research in understanding the application of infobesity at different levels, such as team-levels, within the organization. There is the possibility of acquiring deeper insights of anticipating and overcoming infobesity in varying contexts.

Third, our data was collected prior to the COVID-19 pandemic and hence does not take into account the high frequency and degree of infobesity faced by since the pandemic began. However, we maintain that our research is relevant to business have had to deal with high frequencies of information during the pandemic [47-48]. Furthermore, this paves the way for further investigation to study the impact of frequency of infobesity during crises like the pandemic across international settings [49-50].

6. Conclusion

Infobesity in firms is caused by an abundance of information which is characterised by its intensity and frequency. Recent studies have begun to explore the antecedents of infobesity such as the impact of frequent interactions on consumers' cognitive load. However, there remains a need to understand whether and how the frequency of experiencing infobesity from enterprise systems creates impacts the degree of infobesity experienced by organizations.

In this study we use a research design that integrates inductive analytics and abductive discovery to open the black box of infobesity by comprehensively explaining the complex interplay of multiple levels of predictors, specifically frequency of infobesity, that influence the firm's infobesity experience. We find that experiencing infobesity very rarely does not expose the firm to harsh degrees on infobesity, however constantly experiencing infobesity is likely to leave the firm exposed to high degrees of infobesity.

We conclude that the rate at which firms' decision makers encounter infobesity drives the perception of the degree at which the overload will be experienced.

7. References

[1] P. Hemp, "Death by information overload," *Harvard Business Review,* vol. 87, no. 9, pp. 82-9, 121, 2009.

[2] M. J. Eppler and J. Mengis, "The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines," *Information Society,* vol. 20, no. 5, pp. 325-344, 2004.

[3] T. W. Jackson and P. Farzaneh, "Theory-based model of factors affecting information overload," *International Journal of Information Management,* vol. 32, no. 6, pp. 523-532, 2012.

[4] P. Karhade and J. Q. Dong, "Innovation outcomes of digitally enabled collaborative problemistic search capability," *MIS Quarterly,* vol. 45, no. 2, pp. 693-718, 2021.

[5] A. Gupta, H. Li, and R. Sharda, "Should I send this message? Understanding the impact of interruptions, social hierarchy and perceived task complexity on user performance and perceived workload," *Decision Support Systems,* vol. 55, no. 1, pp. 135-145, 2013.

[6] H. Liang and K.-w. Fu, "Information overload, similarity, and redundancy: Unsubscribing information sources on Twitter," *Journal of Computer-Mediated Communication,* vol. 22, no. 1, pp. 1-17, 2017.

[7] H. Hong and H. J. Kim, "Antecedents and Consequences of Information Overload in the COVID-19 Pandemic," *International Journal of Environmental Research and Public Health,* vol. 17, no. 24, p. 9305, 2020.

[8] P. Karhade and A. Kathuria, "Missing Impact of Ratings on Platform Participation in India: A Call for Research in GREAT Domains," *Communications of the Association for Information Systems,* vol. 47, no. 1, p. 19, 2020.

[9] P. Karhade, M. J. Shaw, and R. Subramanyam, "Patterns in information systems portfolio prioritization," *MIS Quarterly,* vol. 39, no. 2, pp. 413-434, 2015.

[10] A. Kathuria, P. P. Karhade, and B. R. Konsynski, "In the realm of hungry ghosts: Multi-level theory for supplier participation on digital platforms," *Journal of Management Information Systems,* vol. 37, no. 2, pp. 396-430, 2020.

[11] W. Ocasio, "Towards an attention-based view of the firm," *Strategic Management Journal,* vol. 18, no. S1, pp. 187-206, 1997.

[12] M. Tarafdar, Q. Tu, and T. Ragu-Nathan, "Impact of technostress on end-user satisfaction and performance," *Journal of Management Information Systems,* vol. 27, no. 3, pp. 303-334, 2010.

[13] J.-F. Stich, M. Tarafdar, P. Stacey, and S. C. Cooper, "Appraisal of email use as a source of workplace stress: A person-environment fit approach," *Journal of the Association for Information Systems,* vol. 20, no. 2, p. 2, 2019.

[14] P. Karhade, A. Kathuria, O. Malik, and B. Konsynski, "Digital Platforms and Infobesity: A Research Agenda," in The Role of e-Business during the Time of Grand Challenges. WeB 2020. Lecture Notes in Business Information Processing, A. Garimella, P. Karhade, A. Kathuria, X. Liu, J. Xu, and K. Zhao Eds. Cham: Springer 2021, pp. 67-74.

[15] A. Edmunds and A. Morris, "The problem of information overload in business organisations: A review of the literature.," *International Journal of Information Management,* vol. 20, no. 1, pp. 17-28, 2000.

[16] M. Andrade, T. Saldanha, J. Khuntia, A. Kathuria, and W. Boh, "Overcoming Deficiencies for Innovation in SMEs: IT for Closed Innovation versus IT for Open Innovation," in *International Conference on Information Systems*, 2020.

[17] J. Dong, P. Karhade, A. Rai, and X. Xu, "How firms make information technology investment decisions: Toward a behavioral agency theory," *Journal of Management Information Systems,* vol. 38, no. 1, pp. 29-58, 2021.

[18] J. Q. Dong, P. Karhade, A. Rai, and S. X. Xu, "Information Technology and Innovation Outputs: The Missing Link of Search Evolution," in *Academy of Management Proceedings*, 2015.

[19] T. Saldanha, A. Kathuria, J. Khuntia, and B. Konsynski, "Ghosts in the Machine: How Marketing and Human Capital Investments Enhance Customer Growth when Innovative Services Leverage Self-Service Technologies," *Information Systems Research*, vol. (in press), 2021

[20] M. G. Andrade Rojas and A. Kathuria, "Competitive Brokerage: External Resource Endowment and Information Technology as Antecedents," in *Academy of Management Proceedings*, 2014.

[21] T. Ramakrishnan, A. Kathuria, and J. Khuntia, "Business Analytics Capability and Supply Chain Management," *Americas Conference on Information Systems*, 2018.

[22] T. Ramakrishnan, J. Khuntia, A. Kathuria, and T. J. Saldanha, "Business intelligence capabilities," in *Analytics and Data Science*: Springer, 2018, pp. 15-27.

[23] J. Q. Dong, J. He, and P. Karhade, "The Penrose effect in resource investment for innovation: Evidence from information technology and human capital," in *European Conference on Information Systems*, 2013.

[24] J. Q. Dong, P. Karhade, A. Rai, and S. X. Xu, "Dynamic adjustment of information technology, corporate governance, and firm profitability," in *European Conference on Information Systems*, 2013.

[25] J. Q. Dong, P. Karhade, A. Rai, and S. X. Xu, "Information technology in innovation activity of the firm: Theory and synthesis," in *European Conference on Information Systems*, 2013.

[26] S. Mithas, N. Ramasubbu, and V. Sambamurthy, "How Information Management Capability Influences Firm Performance," *MIS Quarterly,* vol. 35, pp. 237-256, 2011.

[27] T. Ramakrishnan, A. Kathuria, and T. J. Saldanha, "Business Intelligence and Analytics (BI&A) Capabilities in Healthcare," in *Theory and Practice of Business Intelligence in Healthcare*: IGI Global, 2020, pp. 1-17.

[28] T. Ramakrishnan, J. Khuntia, A. Kathuria, and T. J. Saldanha, "An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance," *Communications of the Association for Information Systems,* vol. 46, no. 1, p. 31, 2020.

[29] J. Gómez, I. Salazar, and P. Vargas, "Does information technology improve open innovation performance? An Examination of Manufacturers in Spain," *Information Systems Research,* vol. 28, no. 3, pp. 661-675, 2017.

[30] L. Kleis, P. Chwelos, R. V. Ramirez, and I. Cockburn, "Information technology and intangible output: The impact of IT investment on innovation productivity," *Information Systems Research,* vol. 23, no. 1, pp. 42-59, 2012.

[31] A. Rai, R. Patnayakuni, and N. Seth, "Firm performance impacts of digitally enabled supply chain integration capabilities," *MIS Quarterly,* pp. 225-246, 2006.

[32] C. A. Un, A. Cuervo-Cazurra, and K. Asakawa, "R&D collaborations and product innovation," *Journal of Product Innovation Management,* vol. 27, no. 5, pp. 673-689, 2010.

[33] D. Faems, B. Van Looy, and K. Debackere, "Interorganizational collaboration and innovation: Toward a portfolio approach," *Journal of Product Innovation Management,* vol. 22, no. 3, pp. 238-250, 2005.

[34] M. Magni and L. Maruping, "Unleashing innovation with collaboration platforms," *MIT Sloan Management Review,* vol. 60, no. 3, pp. 1-5, 2019.

[35] L. M. Maruping and M. Magni, "Motivating employees to explore collaboration technology in team contexts," *MIS Quarterly,* vol. 39, no. 1, pp. 1-16, 2015.

[36] H. Mendelson and R. R. Pillai, "Industry clockspeed: Measurement and operational implications," *Manufacturing & Service Operations Management,* vol. 1, no. 1, pp. 1-20, 1999.

[37] P. G. Roetzel, "Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development," *Business Research,* vol. 12, no. 2, pp. 479-522, 2019.

[38] H. A. Simon, "Designing organizations for an information-rich world," *International Library of Critical Writings in Economics,* vol. 70, pp. 187-202, 1996.

[39] T. Ragu-Nathan, M. Tarafdar, B. S. Ragu-Nathan, and Q. Tu, "The consequences of technostress for end users in organizations: Conceptual development and empirical validation," *Information Systems Research,* vol. 19, no. 4, pp. 417-433, 2008.

[40] S. McCoy, A. Everard, P. Polak, and D. F. Galletta, "The effects of online advertising," *Communications of the ACM,* vol. 50, no. 3, pp. 84-88, 2007.

[41] P. Karhade and M. Shaw, "Rejection and selection decisions in the IT portfolio composition process: An enterprise risk management based perspective," in *Americas Conference on Information Systems,* 2007.

[42] I. Douven, E. N. Zalta, Ed. *Abduction* (The Stanford Encyclopedia of Philosophy (Summer 2021 Edition)). Metaphysics Research Lab, Stanford University, 2021.

[43] A. Dasgupta, P. Karhade, A. Kathuria, and B. Konsynski, "Holding Space for Voices that Do Not Speak: Design Reform of Rating Systems for Platforms in GREAT Economies," in *Hawaii International Conference on System Sciences*, 2021, p. 2564.

[44] P. Karhade, A. Kathuria, and B. Konsynski, "When Choice Matters: Assortment and Participation for Performance on Digital Platforms," in *Hawaii International Conference on System Sciences*, 2021.

[45] J. Khuntia, T. Saldanha, and A. Kathuria, "Dancing in the tigers' den: MNCs versus local firms leveraging IT-enabled strategic flexibility," in *International Conference on Information Systems*, 2014.

[46] M. Andrade Rojas, A. Kathuria, and B. Konsynski, "Competitive Brokerage: How Information Management Capability and Collaboration Networks Act as Substitutes," Journal of Management Information Systems, vol. Forthcoming, 2021.

[47] S. Vijaykar and P. Karhade, "Remote Virtual Workplaces in the Pandemic: The Case of IT-enabled Service Leadership," in Pacific Asia Conference on Information Systems, 2021.

[48] S. Vijaykar, P. Karhade, and M. Gupta, "Work-From-Home vs. Work-At-Home: A Strategic Conundrum in the Digital Age," in Americas Conference on Information Systems, 2021.

[49] M. Andrade Rojas, T. Saldanha, J. Khuntia, A. Kathuria, and W. F. Boh, "Overcoming Innovation Deficiencies in Mexico: Use of Open Innovation through IT and Closed Innovation through IT by Small and Medium Enterprises," in Hawaii International Conference on System Sciences, 2021, p. 617.

[50] J. Khuntia, A. Kathuria, M. G. Andrade-Rojas, T. Saldanha, and N. Celly, "How Foreign and Domestic Firms Differ in Leveraging IT-enabled Supply Chain Information Integration in BOP Markets: The Role of Supplier and Client Business Collaboration," Journal of the Association for Information Systems, vol. 22, no. 3, 2021.